Mathematica Project: Analysis of Kiva Loans



Insights from Loans disbursed by Kiva

Kiva is a non-profit organization that allows people to lend money via the internet to low-income entrepreneurs. Kiva works with more than 300 microfinance institutions, social impact businesses, schools and non-profit organizations around the world, called "Field Partners" that post profiles of qualified local entrepreneurs on the Kiva website. Lenders browse borrower profiles on *kiva.org* and choose an entrepreneur they wish to fund. Lenders can loan money in increments as small as \$25.

With the help of the Mathematica software, we will perform the analysis of '*Kiva Loans*' data. The dataset is obtained from Kaggle and has more than 6 lakhs rows. We will use Mathematica for Exploratory Data Analysis. We will also apply Machine learning techniques such as Random Forests, Logistic Regression etc. for further analysis.

In[*]:= csvdata =

Import["/Users/vipinragashetti/Vipin/Workspace/UCD/semester-I/Mathematica
 for Research/Project/myproject/kiva_loans.csv"];

In[*]:= header = csvdata[[1]]; data = csvdata[[2;;]];

kivaloan = Thread[header → #] & /@ data // Map[Association] // Dataset

id	funded_amount	loan_amount	activity			
653051	300.0	300.0	Fruits & Vegetables			
653 053	575.0	575.0	Rickshaw			
653 068	150.0	150.0	Transportation			
653 063	200.0	200.0	Embroidery			
653 084	400.0	400.0	Milk Sales			
1080148	250.0	250.0	Services			
653 067	200.0	200.0	Dairy			
653 078	400.0	400.0	Beauty Salon			
653 082	475.0	475.0	Manufacturing			
653 048	625.0	625.0	Food Production/Sales			
653 060	200.0	200.0	Rickshaw			
653 088	400.0	400.0	Wholesale			
653 089	400.0	400.0	General Store			
653 062	400.0	400.0	Clothing Sales			
653 075	225.0	225.0	Poultry			
653 054	300.0	300.0	Rickshaw			
653091	400.0	400.0	General Store			
653052	875.0	875.0	Tailoring			
653 066	250.0	250.0	Sewing			
653 080	475.0	475.0	Beauty Salon			

The dataset used for this project is released by Kiva which provides loans to low-income entrepreneurs and students. The dataset contains various variables listed below.

■ id - a unique identifier for each loan sanctioned.

funded_amount - amount that has been disbursed by Kiva to the field agent.

■ loan_amount - amount that has been released to the borrower by the field agent.

activity - low level category for which the loan has been issued. - high level category for which the loan has been issued. sector

use - amount for which loan has been issued

country_code - ISO country code of country in which loan was disbursed - Full country name of country in which loan was disbursed country

■ region - Full region name within the country

currency - The currency in which the loan was disbursed

partner_id - ID of partner organization

posted_time	- the time at which the loan is posted on Kiva by the field agent
disbursed_time	- The time at which the loan is disbursed by the field agent to the borrower
funded_time completely	- The time at which the loan posted to Kiva gets funded by lenders
term_in_months	- The duration for which the loan was disbursed in months
lender_count	- The total number of lenders that contributed to this loan
repayment_status	- categorial variable for repayment status of the sanctioned loan.

Exploratory Data Analysis

```
In[*]:= Dimensions[kivaloan]
Out[\ \circ\ ]=\ \{\ 671\ 205\ ,\ 20\ \}
      The kivaloan dataset has 6,71205 rows and 20 columns.
```

Check if there are any duplicate ids in kivaloan dataset

DuplicateFreeQ[kivaloan[[All, 1]]]

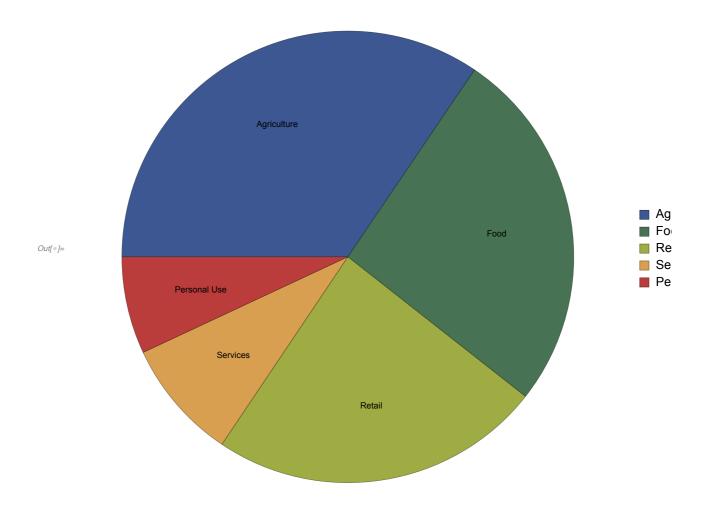
Out[•]= True

There are no duplicate id entries in table.

Pie chart: Sector for which highest loan amount was disbursed

In[*]:= PieChart[Sort[Counts[kivaloan[All, "sector"]], Greater][1;; 5], ChartStyle → "DarkRainbow", ChartLabels → Automatic, ChartLegends → Automatic, PlotLabel → Style["Top 5 Sectors where highest loan amount was disbursed", FontSize → 13.5], ImageSize → Large]

Top 5 Sectors where highest loan amount was disbursed



Finding the highest number of lender count in the dataset

In[*]:= Sort[kivaloan[All, "lender_count"], Greater][1;;1]

2986 Out[•]=

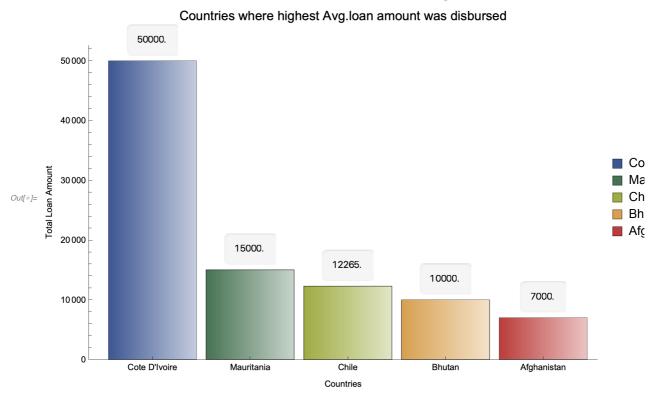
The highest number of lender count in the dataset is 2986.

Bar Chart: Average loan amount disbursed among countries

In[*]:= BarChart

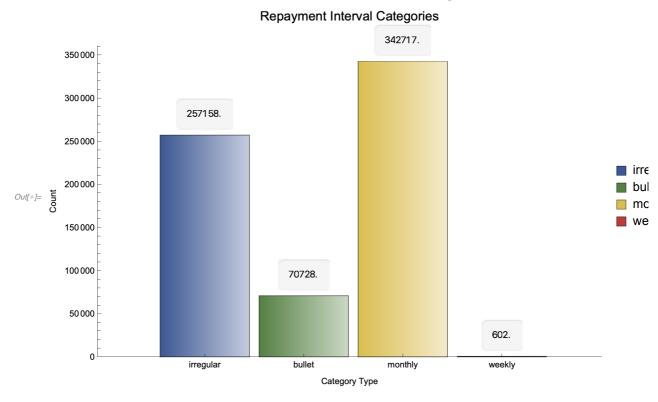
Sort[kivaloan[GroupBy["country"], Mean, "loan_amount"], Greater][1;; 5], ChartStyle → "DarkRainbow", ChartLabels → Automatic, ChartLegends → Automatic, ChartElementFunction → "FadingRectangle", PlotLabel → Style[

"Countries where highest Avg.loan amount was disbursed", FontSize \rightarrow 13.5], LabelingFunction → (Placed[Panel[NumberForm[N@#1]], Above] &), FrameLabel → {{"Total Loan Amount", None}, {"Countries", None}}, Frame → {{True, None}, {True, None}}, ImageSize → Large



Bar Chart: Repayment Interval vs Count

```
In[*]:= BarChart[Counts[kivaloan[All, "repayment_interval"]],
     ChartLabels → Automatic, ChartStyle → "DarkRainbow",
     ChartLegends → Automatic, ChartElementFunction → "FadingRectangle",
     PlotLabel → Style["Repayment Interval Categories", FontSize → 13.5],
     LabelingFunction → (Placed[Panel[NumberForm[N@#1]], Above] &),
     FrameLabel → {{"Count", None}, {"Category Type", None}},
     Frame → {{True, None}, {True, None}}, ImageSize → Large
```



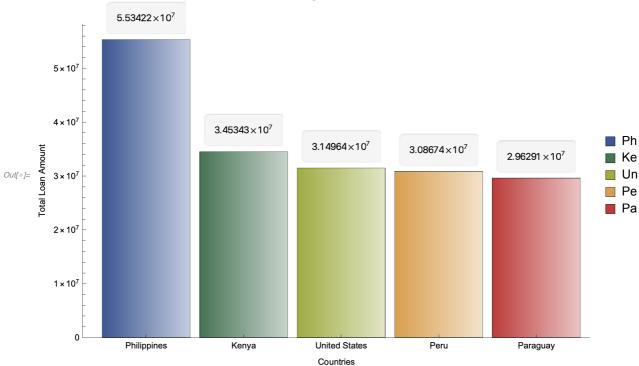
Top 5 Countries where highest total loan amount was disbursed

In[*]:= BarChart

Sort[kivaloan[GroupBy["country"], Total, "loan_amount"], Greater][1;; 5], ChartStyle → "DarkRainbow", ChartLabels → Automatic, ChartLegends → Automatic, ChartElementFunction → "FadingRectangle", PlotLabel → Style[

"Top 5 countries where highest loan amount was disbursed", FontSize \rightarrow 13.5], LabelingFunction → (Placed[Panel[NumberForm[N@#1]], Above] &), FrameLabel → {{"Total Loan Amount", None}, {"Countries", None}}, Frame → {{True, None}, {True, None}}, ImageSize → Large

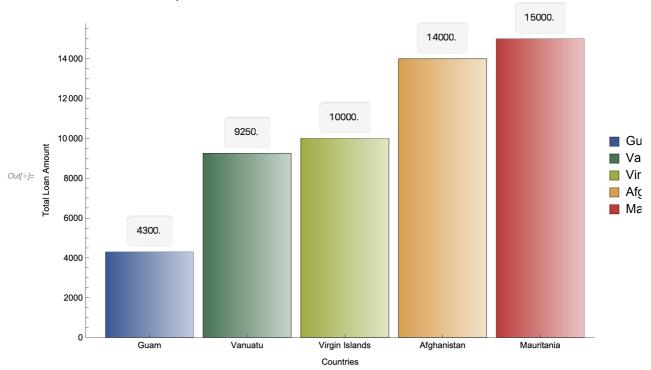




Countries where lowest loan amount was disbursed

```
In[*]:= BarChart[Sort[kivaloan[GroupBy["country"], Total, "loan_amount"]][1;; 5],
     ChartStyle → "DarkRainbow", ChartLabels → Automatic,
     ChartLegends → Automatic, ChartElementFunction → "FadingRectangle", PlotLabel →
      Style["Top 5 countries where lowest total loan amount was disbursed",
       FontSize → 13.5],
     LabelingFunction → (Placed[Panel[NumberForm[N@#1]], Above] &),
     FrameLabel → {{"Total Loan Amount", None}, {"Countries", None}},
     Frame → {{True, None}, {True, None}}, ImageSize → Large
```

Top 5 countries where lowest total loan amount was disbursed

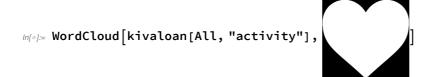


WordCloud generates the word cloud graphics with different sizes based on the multiplicity in given input data

In[*]:= WordCloud[WordCounts[ToString[kivaloan[All, "country"]]]]



Country where highest number of loans/funds raised by Kiva was granted to Philippines followed by Kenya.





Top Activities/Reason for which the loan was granted are General Store, Housing Expenses, Farming.

```
<code>[n[•]:= gender = kivaloan[All, "borrower_genders"];</code>
    Total[StringCount[Normal[gender], "male"]];
    Total[StringCount[Normal[gender], "female"]];
    PieChart3D[{Total[StringCount[Normal[gender], "male"]],
       Total[StringCount[Normal[gender], "female"]]}, ChartStyle → "DarkRainbow",
      ChartLabels → Placed[{"Male", "Female"}, "RadialOuter"]]
Out[ • ]=
```

There are total of 13,46,212 individual male borrowers and 10,71,308 female borrowers.

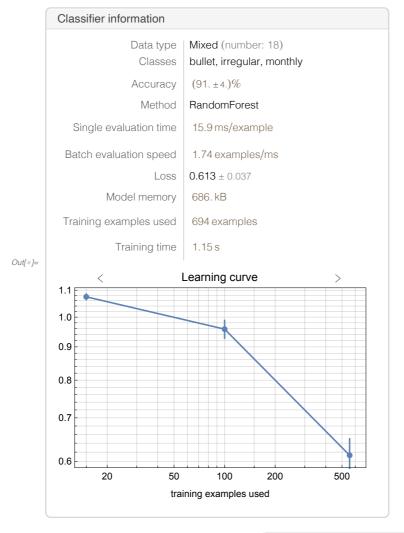
Machine Learning - Classification **Predicting Labelled Data**

```
In[@]:= kivaloan = kivaloan[1;; 400 000];
    train = {};
    test = {};
    For [i = 1, i ≤ Length[kivaloan], i++,
     If[RandomInteger[{1, Length[kivaloan]}] < Length[kivaloan] 70 / 100,</pre>
      AppendTo[train, Normal[kivaloan[i, All]]],
      AppendTo[test, Normal[kivaloan[i, All]]]]
    train = Dataset[train];
    test = Dataset[test];
    Dropping the columns that will not be included in model
In[*]:= train = Dataset[Drop[train[1;; Length[train], Range[1, 19]]]];
    test = Dataset[Drop[test[1;; Length[test], Range[1, 19]]]];
In[•]:= Clear[trainsetFeatures, testsetFeatures]
    train = Drop[train[1;; Length[train], Range[1, 19]]];
    trainsetFeatures = train[1;; Length[train]];
    trainsetFinal =
      Flatten[Normal@trainsetFeatures[1;; Length[train], {Most@# → Last@#} &], 1];
    testsetFeatures = test[1;; Length[test]];
    testsetFinal =
      Flatten[Normal@testsetFeatures[1;; Length[test], {Most@# → Last@#} &], 1];
```

Random Forest

In[*]:= Clear[classifierMeasurements, algoRandomForest] algoRandomForest = Classify[trainsetFinal, Method → "RandomForest"] ClassifierInformation[algoRandomForest] classifierMeasurements = ClassifierMeasurements[algoRandomForest, testsetFinal] classifierMeasurements /@ {"Accuracy", "Error"} // TableForm

Out[*]= ClassifierFunction[Input type: Mixed (number: 18) Classes: bullet, irregular, monthly



 $\mathit{Out}[\ \ \ \ \ \ \ \]=$ ClassifierMeasurementsObject



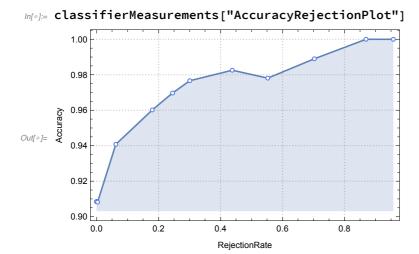
Out[]//TableForm=

0.908497

0.0915033

The accuracy of the Random Forest Model is 91% and error produced by the model is 0.09%

Now lets plot the Accuracy Rejection Model



Classifying the labelled data. We are here trying to classify the repayment interval. The repayment interval can be of 3 types: Weekly, bullet, Irregular, monthly.

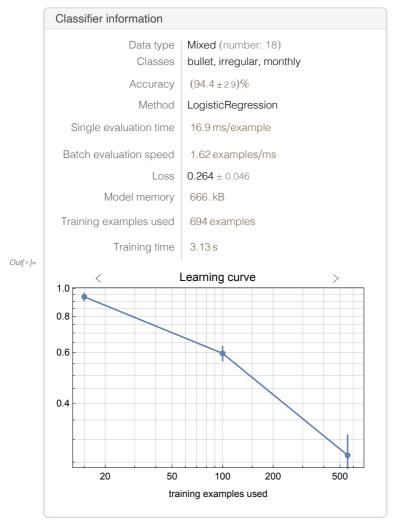
```
ln[\cdot]:= algoRandomForest[\langle | \text{"id"} \rightarrow 653\,051, \text{"funded_amount"} \rightarrow 300.`,
       "loan_amount" → 300.`, "activity" → "Fruits & Vegetables", "sector" → "Food",
       "use" → "To buy seasonal, fresh fruits to sell. ", "country_code" → "PK",
       "country" → "Pakistan", "region" → "Lahore", "currency" → "PKR",
       "partner_id" → 247.`, "posted_time" → "2014-01-01 06:12:39+00:00",
       "disbursed_time" → "2013-12-17 08:00:00+00:00",
       "funded_time" → "2014-01-02 10:06:32+00:00", "term_in_months" → 12.`,
       "lender_count" → 12, "tags" → "", "borrower_genders" → "female" |> ]
Out[*]= irregular
```

The repayment interval classified above is "Irregular" for the given user input for built Random Forest model.

Logistic Regression

In[*]:= Clear[classifierMeasurements, algoLogisticRegression] algoLogisticRegression = Classify[trainsetFinal, Method → "LogisticRegression"] ClassifierInformation[algoLogisticRegression] classifierMeasurements = ClassifierMeasurements[algoLogisticRegression, testsetFinal] classifierMeasurements /@ {"Accuracy", "Error"} // TableForm

Out[*]= ClassifierFunction[Input type: Mixed (number: 18) Classes: bullet, irregular, monthly



 $\textit{Out} [@ \textit{\textit{j}} = \texttt{ClassifierMeasurementsObject} \\$

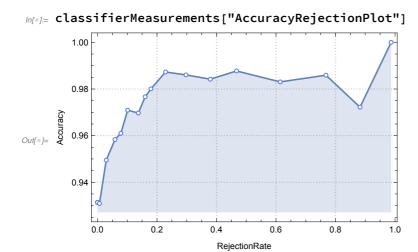


Out[]//TableForm=

0.931373

0.0686275

The accuracy of the Random Forest Model is 93% and error produced by the model is 0.06% Now lets plot the Accuracy Rejection Model



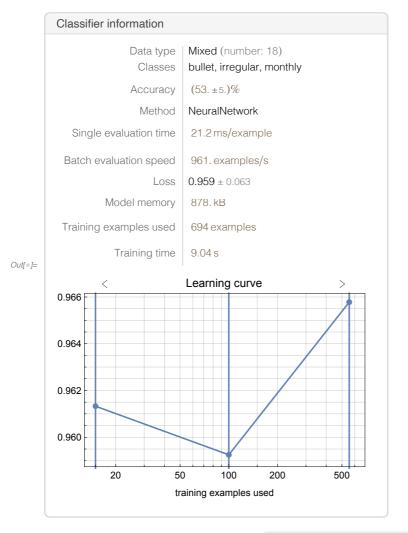
Classifying the labelled data on the trained Logistic Regression model.

```
m_{\text{o}} = \text{algoLogisticRegression} \left( \left| \text{"id"} \rightarrow 653089, \text{"funded_amount"} \rightarrow 400. \right| \right)
        "loan_amount" → 400.`, "activity" → "General Store", "sector" → "Retail",
        "use" \rightarrow "to buy stock of rice, sugar and flour .", "country_code" \rightarrow "PK",
        "country" → "Pakistan", "region" → "Faisalabad", "currency" → "PKR",
        "partner_id" → 245.`, "posted_time" → "2014-01-01 12:04:57+00:00",
        "disbursed_time" → "2013-12-24 08:00:00+00:00",
        "funded_time" \rightarrow "2014-01-08 00:35:14+00:00",
        "term_in_months" → 14.`, "lender_count" → 16,
        "tags" → "#Repeat Borrower, #Woman Owned Biz", "borrower_genders" → "female" |> ]
Out[*]= monthly
```

Neural Network

In[*]:= Clear[algoNeuralNetwork, classifierMeasurements] algoNeuralNetwork = Classify[trainsetFinal, Method → "NeuralNetwork"] ClassifierInformation[algoNeuralNetwork] classifierMeasurements = ClassifierMeasurements[algoNeuralNetwork, testsetFinal] classifierMeasurements /@ {"Accuracy", "Error"} // TableForm

Out[*]= ClassifierFunction[Input type: Mixed (number: 18) Classes: bullet, irregular, monthly



Classifier: NeuralNetwork Out[*]= ClassifierMeasurementsObject[Number of test examples: 306 Data not in notebook; Store now »

Out[•]//TableForm=

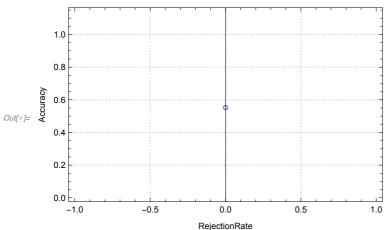
0.552288

0.447712

The accuracy of the Neural Network Model is 55% and error produced by the model is 44%. This is not the good model for kiva loan data as the accuracy is less.

Plot for the Accuracy Rejection Model

In[*]:= classifierMeasurements["AccuracyRejectionPlot"]



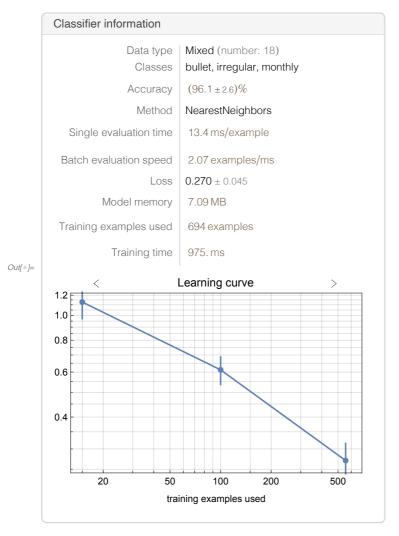
Classifying the labelled trained data on the Logistic Neural Network model.

```
ln[@]:= algoNeuralNetwork [\langle |"id" \rightarrow 653089, "funded_amount" \rightarrow 400.`,]
       "loan_amount" → 400.`, "activity" → "General Store", "sector" → "Retail",
       "use" → "to buy stock of rice, sugar and flour .", "country_code" → "PK",
       "country" → "Pakistan", "region" → "Faisalabad", "currency" → "PKR",
       "partner_id" → 245.`, "posted_time" → "2014-01-01 12:04:57+00:00",
       "disbursed_time" → "2013-12-24 08:00:00+00:00",
       "funded time" → "2014-01-08 00:35:14+00:00",
       "term_in_months" → 14.`, "lender_count" → 16,
       "tags" → "#Repeat Borrower, #Woman Owned Biz", "borrower_genders" → "female" |> ]
Out[*]= monthly
```

Nearest Neighbors

In[*]:= Clear[classifierMeasurements, algoNearestNeighbors] algoNearestNeighbors = Classify[trainsetFinal, Method → "NearestNeighbors"] ClassifierInformation[algoNearestNeighbors] classifierMeasurements = ClassifierMeasurements[algoNearestNeighbors, testsetFinal] classifierMeasurements /@ {"Accuracy", "Error"} // TableForm





Classifier: NearestNeighbors Out[*]= ClassifierMeasurementsObject Number of test examples: 306 Data not in notebook; Store now »

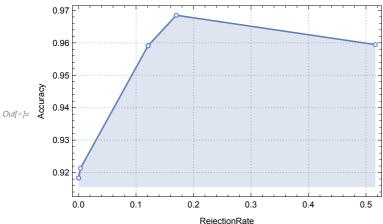
Out[•]//TableForm=

0.918301

0.0816993

The accuracy of the Nearest Neighbors Model is 92% and error produced by the model is 8%.





Classifying the labelled trained data on the Nearest Neighbors model.

```
logius = 1 algoNearestNeighbors [\langle | \text{"id"} \rightarrow 653208, \text{"funded_amount"} \rightarrow 500.`,]
       "loan_amount" → 500.`, "activity" → "Cereals", "sector" → "Food",
       "use" → "to buy cereals to increase his stock", "country_code" → "KE",
       "country" → "Kenya", "region" → "Nanyuki", "currency" → "KES",
       "partner_id" → 203.`, "posted_time" → "2014-01-02 08:03:33+00:00",
       "disbursed_time" → "2013-12-11 08:00:00+00:00",
       "funded_time" -> "2014-01-29 16:09:50+00:00",
       "term_in_months" → 14.\`, "lender_count" → 20,
       "tags" → "#Elderly, #Repeat Borrower, user_favorite, user_favorite",
       "borrower_genders" → "male" |> ]
Out[*]= irregular
```

Geographic Plotting

```
In[*]:= dhsmpi =
      Import["/Users/vipinragashetti/Vipin/Workspace/UCD/semester-I/Mathematica
          for Research/Project/myproject/dhs_mpi_loan.csv"];
    header = dhsmpi[[1]];
    data = dhsmpi[[2;;]];
    dhsmpi = Thread[header → #] & /@ data // Map[Association];
    dhsmpi = Dataset[dhsmpi];
    Converting the latitude and longitude from degrees to radians.
```

```
location = location 
                                        dhsmpi = dhsmpi[All, Append[\#, "lonradian" \rightarrow N[0.017 * (\#"lon"), 5]] &];
                                        dhsmpi = dhsmpi[All, Append[#, "latlon" → {#"latradian", #"lonradian"}] &];
                                        dhsmpi[[1;;]]
```

	DHS	Partr	Field	sectc	Loan	Loan
1	366	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOr8	Control G
2	366	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000006Tm5J	Single mo
3	366	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000000wf0w	General
4	366	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOqt	Flexible lo
5	366	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000006Tm4k	Unbanke
6	366	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOqz	Flexible I
7	366	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000006Tm59	Youth En
8	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000006Tm59	Youth En
9	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOqz	Flexible I
10	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000000wf0w	General
11	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOqt	Flexible I
12	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000000wf0w	General
13	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOqt	Flexible I
14	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOr8	Control G
15	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000006Tm4k	Unbanke
16	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000006Tm5J	Single m
17	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000000wf0w	General
18	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOqt	Flexible I
19	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOr8	Control C
20	443	154	FundaciÍ_n Mario Santo Domingo (FMSD)	Other	a1050000002ZOr8	Control G

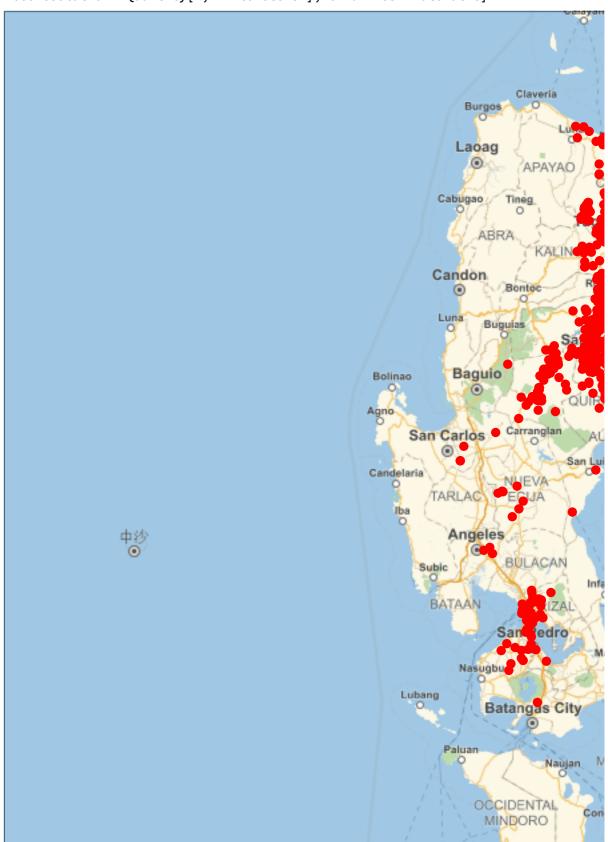
Plotting the points on the Interactive map where the loans was distributed by Kiva

```
ln[w]:= f[x_, y_] := (\{x[[\#]], y[[\#]]\}) \& /@Range[Min[Length[x], Length[y]]];
     coord = f[dhsmpi[All, "lat"], dhsmpi[All, "lon"]];
m_{\text{o}} = \text{DynamicGeoGraphics}[\{0\text{range}, \text{PointSize}[Large}], \text{Point@GeoPosition@coord}\},
      GeoRange → "World", GeoProjection → "Robinson"]
Out[ • ]=
```

Plotting the Interactive Map of Philippines where highest number of loans were distributed.

[Map requires Internet connection to get loaded]

In[@]:= DynamicGeoGraphics[{Red, PointSize[Large], Point@GeoPosition@coord}, GeoRange → Entity["Country", "Philippines"], GeoResolution → Quantity[1, "Kilometers"], GridLines → Automatic]

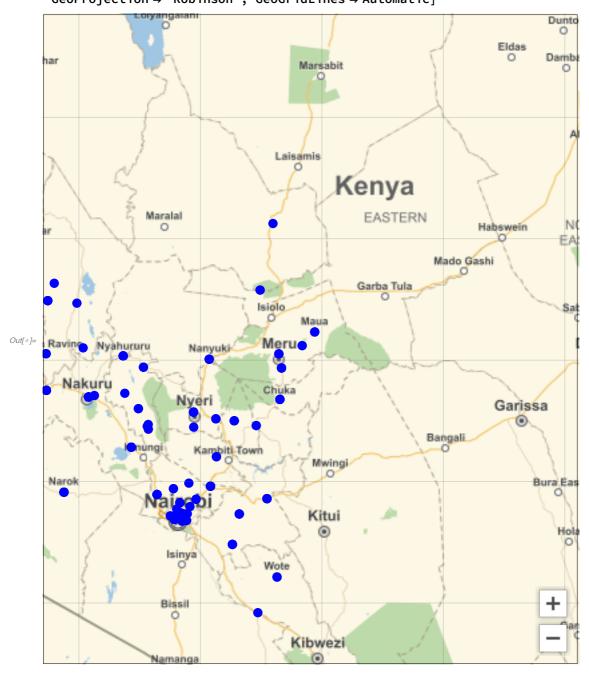






Plotting the Interactive map for Kenya where loans were distributed [Map requires Internet connection to get loaded]

In[@]:= DynamicGeoGraphics[{Blue, PointSize[Large], Point@GeoPosition@coord}, GeoRange → Entity["Country", "Kenya"], GeoProjection → "Robinson", GeoGridLines → Automatic]



Machine Learning - Prediction Predicting Unlabelled Data

In dhs_mpi_loan.csv, the countries are grouped into clusters and contains the geographic locations like latitude and longitude where the loan was disbursed. We will try to build the model using these geographic parameters and try to predict the cluster id. This data is provided my 'The Demographic and Health Surveys Program' (DHS) which is responsible for collecting and disseminating accurate, nationally representative data on health and population in developing countries.

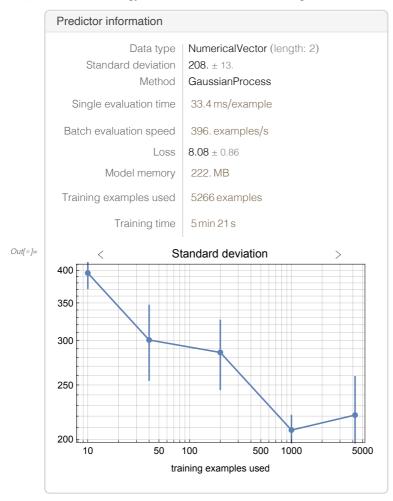
We will be using the predict function which is used to predict/classify the unlabelled continuous data.

```
In[*]:= traindata = {};
    For[i = 1, i ≤ Length[dhsmpi], i++, list = AppendTo[traindata,
       Normal[dhsmpi[i, "latlon"]] → Normal[dhsmpi[i, "DHSCLUST"]]]]
```

Gaussian Process

<code>m[*]:= predictGaussianProcess = Predict[traindata, Method → "GaussianProcess"]</code> Out[*]= PredictorFunction[Input type: NumericalVector (length: 2) Method: GaussianProcess Data not in notebook; Store now »

In[*]:= Information[predictGaussianProcess]



Predicting the Cluster Id when the latitude is 4.19158 and longitude is -1.313 using Linear Regression model

In[*]:= predictGaussianProcess[{4.19158, -1.313}]

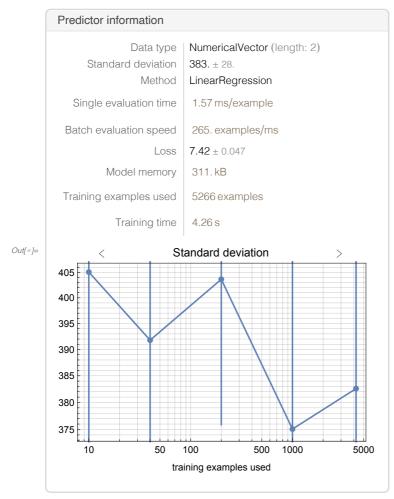
Out[*]= 572.933

Linear Regression

In[*]:= predictLinearRegression = Predict[traindata, Method → "LinearRegression"]



In[*]:= Information[predictLinearRegression]



Predicting the Cluster Id when the latitude is 0.19058 and longitude is -1.30563 using Linear Regression model

In[*]:= predictLinearRegression[{0.19058, -1.30563}] Out[*]= 1395.44

Random Forest

<code>In[*]:= predictRandomForest = Predict[traindata, Method → "RandomForest"]</code>

Input type: NumericalVector (length: 2) Out[*]= PredictorFunction[Method: RandomForest

In[@]:= Information[predictRandomForest]



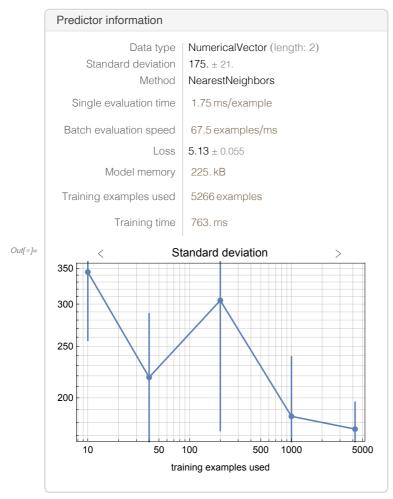
Predicting the Cluster Id when the latitude is 10.1801 and longitude is -1.401 using Random Forest model

In[*]:= predictRandomForest [{10.1801, -1.401}] Out[*]= 754.799

Nearest Neighbors

In[*]:= predictNearestNeighbors = Predict[traindata, Method → "NearestNeighbors"] Input type: NumericalVector (length: 2) Out[*]= PredictorFunction Method: NearestNeighbors

In[*]:= Information[predictNearestNeighbors]



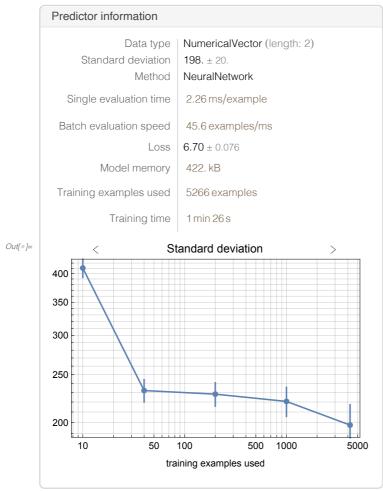
Predicting the Cluster Id when the latitude is 11.1791 and longitude is -1.234 using Nearest Neighbors model

In[*]:= predictNearestNeighbors[{11.1791, -1.234}] Out[•]= 291.

Neural Network

In[*]:= predictNeuralNetwork = Predict[traindata, Method → "NeuralNetwork"] Input type: NumericalVector (length: 2) Method: NeuralNetwork

In[@]:= Information[predictNeuralNetwork]



Predicting the Cluster Id when the latitude is 7.234 and longitude is -0.173 using Nearest Neighbors model

In[*]:= predictNeuralNetwork[{7.234, -0.173}] Out[*]= 6329.1

Conclusion

Exploratory Data Analysis Summary

- The country where highest amount of kiva loans was disbursed is *Philippines* followed by *Kenya* and United States.
- Large number of people are regular/monthly in the loan repayment. We also notice from the bar chart that there are significant people who are irregular in repaying the loan.
- Highest number of loans was disbursed for *Agriculture* sector followed by *food* and *retail*.
- The country where lowest amount of loan was disbursed was *Guam*.
- The country where with highest average loan amount is *Cote D'Ivoire*.

Machine Learning- Training, Classification and Prediction

Classification is used to classify the labelled data. Here were are trying to classify the repayment interval on the data. I have selected the first 4 lakhs records since mathematica software was crashing intermittently and was taking more time to build models.

Here the data is divided into train and test subset and various Machine Learning techniques are applied on the train data and the model is tested using test data. We notice from the above models that Accuracy of classification is highest for Nearest Neighbors and Logistic Regression. These models are best models when you are trying to predict the labelled/discrete data. Neural Network performed bad for this dataset and is more suitable for very large and continuous type of response variable.

Prediction technique is used to predict unlabelled/continuous data. We have used another dataset provided by DHS (Demographic and Health Surveys). Different countries together form a cluster and have a cluster id. We are trying to predict the cluster id when the latitude and longitude is provided as input to the model.

We have built the different models and predicted the cluster id from the trained model.

We have gained so many outcomes and insights from the Kiva crowd funded loan platform. Machine Learning and Exploratory Data Analysis can be performed in Mathematica software with ease. Machine Learning techniques like classification and prediction can be performed with a single command even though it takes some time for processing.

In this project, I have learned how to analyse, build models, classify and predict the data in Mathematica, in addition to its computation capabilities.

Mathematica is a user friendly application/software for Data Analysis and Machine Learning.