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| Practical Data Science |
| Project report |
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**12/19/2012**

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Summary

**Data Source**

Kiva

URL: <http://build.kiva.org/>

Kiva provides a RESTful Web-service API for accessing data on lenders, loans and other related Kiva objects. Kiva API returns the response in XML and JSON formats depending on the URL accessed. We downloaded the bulk data provided by Kiva from the URL <http://s3.kiva.org/snapshots/kiva_ds_json.zip> to do an initial analysis of the data and came up with a few models and questions that we can answer with the data. We installed MySQL community edition database on our laptop and created a training and test database with tables for the major kiva objects. We loaded the bulk data for lenders and loans using python. We also created python scripts to fetch some live data from Kiva API and loaded that data as well into the training and test databases to ensure that the models apply to old as well as new data. We also loaded other tables such as country, loan->lenders and lender -> loans to analyze the relationships between the objects.

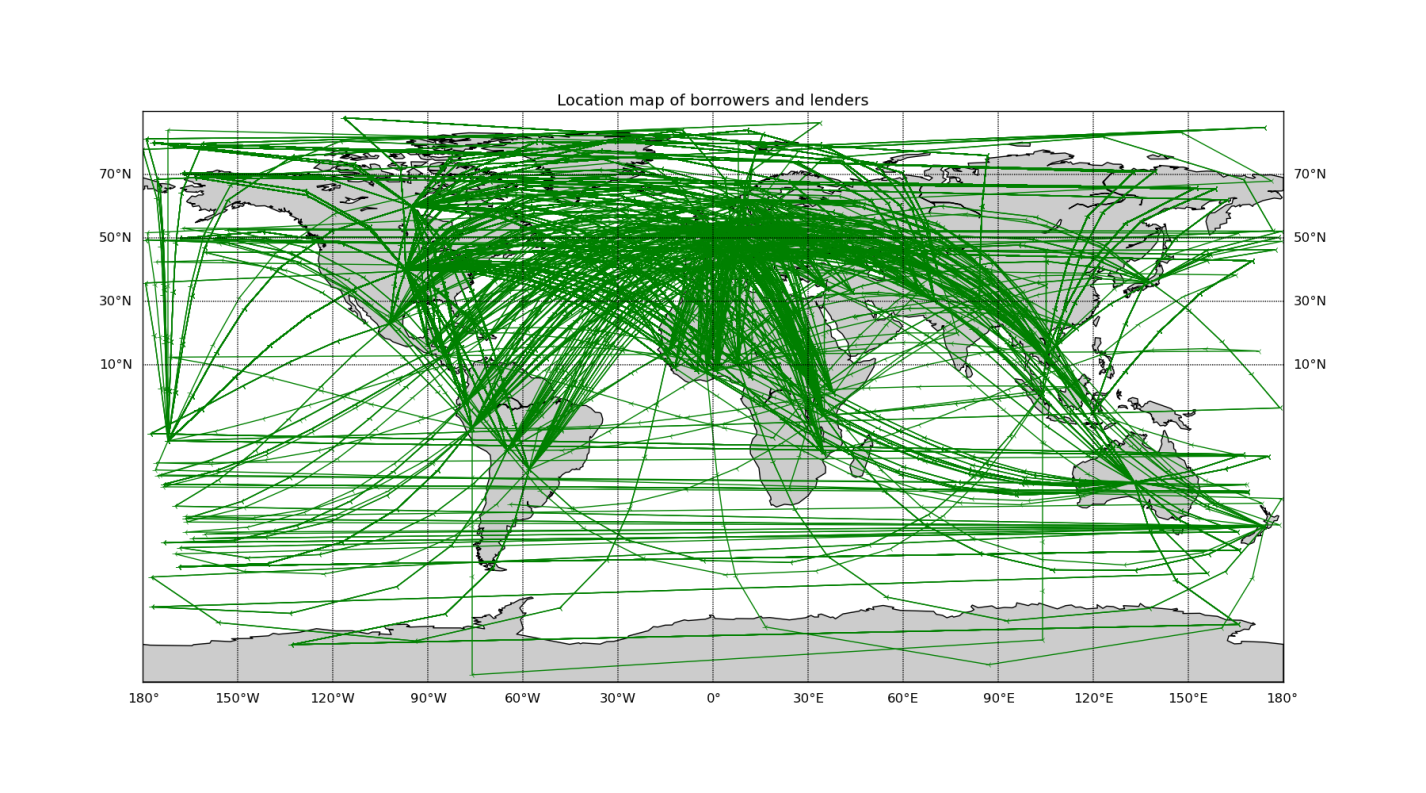
We reused some of the data model from <http://www.kivadata.org/> website.

**Mapping locations of lenders and borrowers**

We used the python map visualization library Basemap to plot the locations of lenders and borrowers and project the trend in kiva loans. Using the Kiva API we loaded all the lenders for a loan and used the country data from loan and lender objects to plot the map.

**Python module**: map\_loan\_countries.py

The most glaring aspect of this visualization is that Africa seems to be the region with most borrowers and North America seems to be the region with most lenders, which is not surprising. South America and Mexico also have a high number of borrowers. Some of the South East Asian countries are also heavily active in kiva. Please note that the python library we used has a glitch which cannot draw the lines when the lines end and re-enter from the other side. These lines appear as straight lines in the bottom.



We could not do a mapping between lenders and borrower’s demographics since data about lender demographics is not available except for their location and occupation.

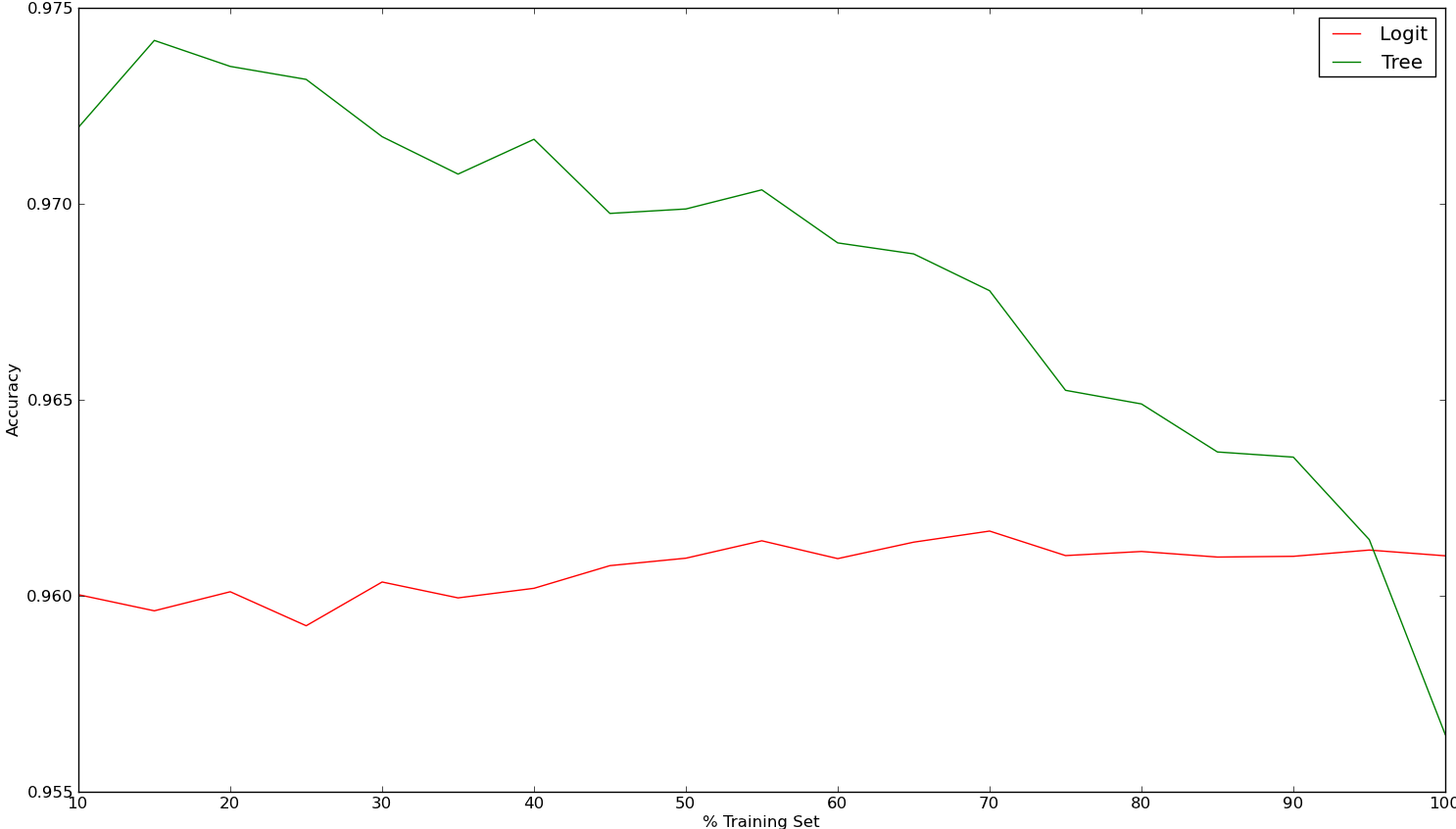
**Predictive model to classify a specific loan as whether it will be fully funded or not:**

We used certain parameters such as loan\_amount, paid\_amount, funded\_amount, disbursal\_amount, sector, partner\_id and gender as inputs to the predictive model to determine whether a particular loan will be fully funded or not. We realize that the factors used are small in number, related and do not capture all the parameters that would determine the possibility of a loan being funded.

However we used Logistic regression and decision tree models to determine the probability and used cross\_validation to test the models with a varying size of training and test data sets.

**Python module: model.py**

The comparative plot of the accuracy of the models with the change in size of training and test data sets is shown below:



**Analysis of the loans based on sector, activity, country and gender**

We used the data in the training database and SQL queries to analyze the influence of sector, activity, country and gender in how loans are funded.

Following table lists the loan sectors ordered by % of fully funded loans:

|  |  |  |  |
| --- | --- | --- | --- |
| **Sector** | **Funded** | **Not funded** | **% Funded** |
| Housing | 9047 | 1175 | 88.50518 |
| Personal Use | 3074 | 248 | 92.53462 |
| Clothing | 22617 | 1276 | 94.65952 |
| Transportation | 11064 | 599 | 94.8641 |
| Retail | 75379 | 4026 | 94.92979 |
| Agriculture | 67459 | 3419 | 95.17622 |
| Services | 25878 | 1193 | 95.59307 |
| Food | 85674 | 3610 | 95.95672 |
| Wholesale | 805 | 32 | 96.17682 |
| Construction | 6478 | 211 | 96.84557 |
| Health | 2734 | 79 | 97.19161 |
| Entertainment | 599 | 15 | 97.557 |
| Education | 2838 | 70 | 97.59285 |
| Arts | 7389 | 167 | 97.78984 |
| Manufacturing | 4601 | 100 | 97.87279 |

Housing, personal use and clothing sectors attract lower fraction of loans while manufacturing, arts, education and healthcare attract relatively higher fraction of loans.

**By country**

Appendix 3 lists the loans to borrowers in each country. Countries such as Gaza, Timor-Leste and Turkey have a very high proportion of funded loans. In contrast, Bangladesh, Jordan and Zambia receive a low fraction of fully funded loans.

Among the top 10 countries with most number of loans, Ghana and Mexico have a high ratio of funded loans. Tajikistan and Uganda have a low ratio in the top 10 countries.

**By Gender**

Following table lists the number of loans and the proportion of funded loans by gender

|  |  |  |  |
| --- | --- | --- | --- |
| **Gender** | **Not funded** | **Funded** | **%Funded** |
| F | 7958 | 205389 | 96.26993 |
| M | 5329 | 77520 | 93.56782 |
| N | 2933 | 42727 | 93.57643 |

Female borrowers attract approximately 3% more loans than male borrowers or borrowers of unknown gender.

This shows a clear inclination towards lending to woman.

**By Activity**

There are 149 activities listed under the 15 sectors in Kiva. Appendix 4 lists the number of loans and proportion of funded loans by activity.

Activities such as Machine Shop, Well digging and Renewable Energy Products attract very high proportion of funding. Activities such as Personal Housing Expenses, Funeral Expenses, Machinery Rental and Wedding Expenses attract very low proportion of funding.

Among the top 10 activities by total number of loans, Food Production/Sales and

Fruits & Vegetables activities attract a high proportion of funding while Retail and

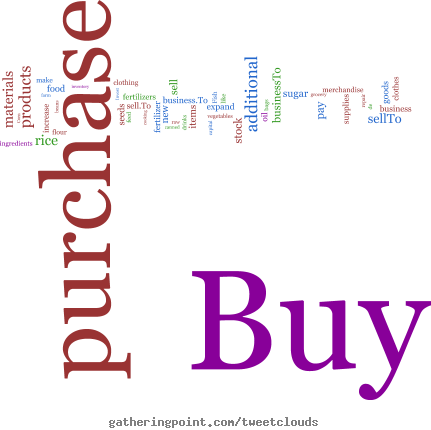
Personal Housing Expenses activities attract a lower proportion.

**Word cloud of lender loaning reason and loan uses:**

In order to find more about what were the most important reasons for a lender providing a loan and the most frequent uses of loans we used the text provided in the loans and lender profiles to create word clouds.

Python module: WordCloudsample.py

Following is the word cloud of the uses of loans:



It is clear that borrowers like to purchase or buy items like rice, sugar, clothing materials.

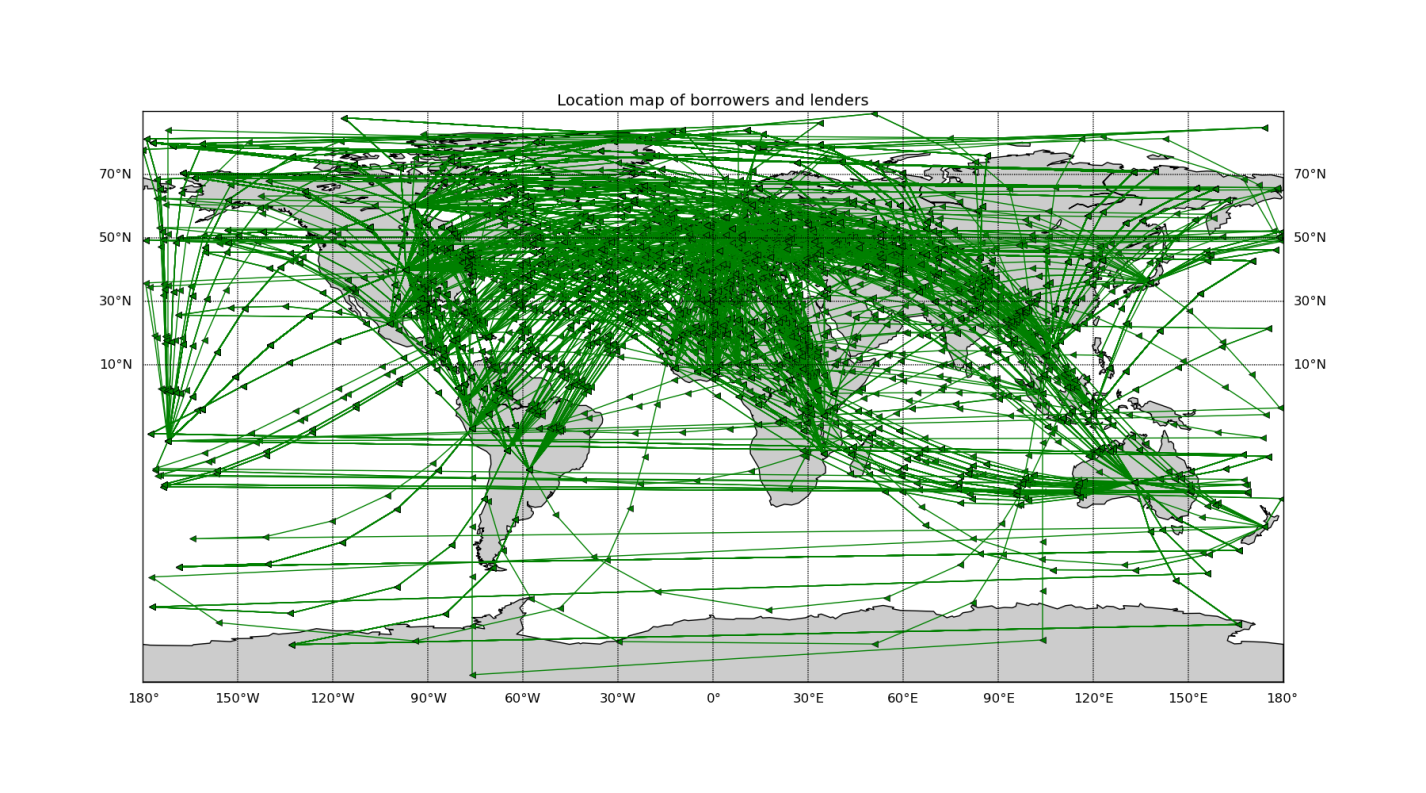
Following is the word cloud of lender’s reasons for providing a loan.



It is clear that lenders want to help people and want to make a difference and believe in others.

Appendix 1

Alternative visualization of location of lenders and borrowers.



Appendix 2:

Output from model.py module, which used logistic regression and decision tree models to predict the possibility of a loan being fully funded:

Number of train records: 171101

Number of test records: 74205

length: 171101

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 171101

Accuracy :0.960888597963

length: 171101

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 171101

Accuracy :0.99722386193

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Evaluating for : 5 %

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Training data#: 162545 Test data#: 8556

length: 8556

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 8556

Accuracy :0.960028050491

length: 8556

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 8556

Accuracy :0.971949509116

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Evaluating for : 10 %

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Training data#: 153990 Test data#: 17111

length: 17111

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 17111

Accuracy :0.959616620887

length: 17111

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 17111

Accuracy :0.974168663433

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Evaluating for : 15 %

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Training data#: 145435 Test data#: 25666

length: 25666

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 25666

Accuracy :0.960102859815

length: 25666

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 25666

Accuracy :0.973505805346

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Evaluating for : 20 %

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Training data#: 136880 Test data#: 34221

length: 34221

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 34221

Accuracy :0.959235557114

length: 34221

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 34221

Accuracy :0.973174366617

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-----------------------------------------------------------------------

Evaluating for : 25 %

-----------------------------------------------------------------------

Training data#: 128325 Test data#: 42776

length: 42776

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 42776

Accuracy :0.960351599027

length: 42776

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 42776

Accuracy :0.971713110155

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-----------------------------------------------------------------------

Evaluating for : 30 %

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Training data#: 119770 Test data#: 51331

length: 51331

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 51331

Accuracy :0.959946231322

length: 51331

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 51331

Accuracy :0.970758411097

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-----------------------------------------------------------------------

Evaluating for : 35 %

-----------------------------------------------------------------------

Training data#: 111215 Test data#: 59886

length: 59886

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 59886

Accuracy :0.960191029623

length: 59886

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 59886

Accuracy :0.971646127643

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-----------------------------------------------------------------------

Evaluating for : 40 %

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Training data#: 102660 Test data#: 68441

length: 68441

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 68441

Accuracy :0.960769129615

length: 68441

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 68441

Accuracy :0.969754971435

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Evaluating for : 45 %

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Training data#: 94105 Test data#: 76996

length: 76996

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 76996

Accuracy :0.960959010858

length: 76996

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 76996

Accuracy :0.969868564601

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Evaluating for : 50 %

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Training data#: 85550 Test data#: 85551

length: 85551

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 85551

Accuracy :0.961403139648

length: 85551

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 85551

Accuracy :0.970356863158

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Evaluating for : 55 %

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Training data#: 76995 Test data#: 94106

length: 94106

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 94106

Accuracy :0.960948292351

length: 94106

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 94106

Accuracy :0.969003039126

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Evaluating for : 60 %

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Training data#: 68440 Test data#: 102661

length: 102661

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 102661

Accuracy :0.961367997584

length: 102661

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 102661

Accuracy :0.968722299607

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Evaluating for : 65 %

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Training data#: 59885 Test data#: 111216

length: 111216

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 111216

Accuracy :0.961651201266

length: 111216

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 111216

Accuracy :0.967783412459

-----------------------------------------------------------------------

-----------------------------------------------------------------------

Evaluating for : 70 %

-----------------------------------------------------------------------

Training data#: 51330 Test data#: 119771

length: 119771

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 119771

Accuracy :0.961025623899

length: 119771

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 119771

Accuracy :0.96524200349

-----------------------------------------------------------------------

-----------------------------------------------------------------------

Evaluating for : 75 %

-----------------------------------------------------------------------

Training data#: 42775 Test data#: 128326

length: 128326

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 128326

Accuracy :0.961130246404

length: 128326

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 128326

Accuracy :0.964894097845

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-----------------------------------------------------------------------

Evaluating for : 80 %

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Training data#: 34220 Test data#: 136881

length: 136881

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 136881

Accuracy :0.960988011484

length: 136881

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 136881

Accuracy :0.963669172493

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-----------------------------------------------------------------------

Evaluating for : 85 %

-----------------------------------------------------------------------

Training data#: 25665 Test data#: 145436

length: 145436

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 145436

Accuracy :0.96100690338

length: 145436

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 145436

Accuracy :0.963537225996

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-----------------------------------------------------------------------

Evaluating for : 90 %

-----------------------------------------------------------------------

Training data#: 17110 Test data#: 153991

length: 153991

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 153991

Accuracy :0.961166561682

length: 153991

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 153991

Accuracy :0.961432811008

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-----------------------------------------------------------------------

Evaluating for : 95 %

-----------------------------------------------------------------------

Training data#: 8555 Test data#: 162546

length: 162546

Model: <class 'sklearn.linear\_model.logistic.LogisticRegression'> No of test records: 162546

Accuracy :0.961020265033

length: 162546

Model: <class 'sklearn.tree.tree.DecisionTreeClassifier'> No of test records: 162546

Accuracy :0.956461555498

Appendix 3

Table listing loans to borrowers in each country

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Country** | **Funded** | **Not funded** | **%Funded** | **Total loans** |
| GZ | 8 | 0 | 100 | 8 |
| TL | 77 | 0 | 100 | 77 |
| TR | 8 | 0 | 100 | 8 |
| BG | 209 | 1 | 99.5238 | 210 |
| CI | 170 | 1 | 99.4152 | 171 |
| BA | 316 | 3 | 99.0596 | 319 |
| UA | 2297 | 25 | 98.9233 | 2322 |
| CD | 706 | 13 | 98.1919 | 719 |
| DO | 2605 | 51 | 98.0798 | 2656 |
| GH | 9076 | 185 | 98.0024 | 9261 |
| QS | 3724 | 80 | 97.897 | 3804 |
| MX | 8223 | 189 | 97.7532 | 8412 |
| PY | 5650 | 134 | 97.6833 | 5784 |
| CL | 495 | 12 | 97.6331 | 507 |
| IL | 112 | 3 | 97.3913 | 115 |
| CG | 435 | 12 | 97.3154 | 447 |
| HT | 143 | 4 | 97.2789 | 147 |
| RW | 4507 | 129 | 97.2174 | 4636 |
| MZ | 1708 | 49 | 97.2112 | 1757 |
| PE | 35826 | 1085 | 97.0605 | 36911 |
| KG | 2306 | 72 | 96.9722 | 2378 |
| ZA | 128 | 4 | 96.9697 | 132 |
| TG | 6313 | 199 | 96.9441 | 6512 |
| VN | 3676 | 117 | 96.9154 | 3793 |
| PH | 49078 | 1573 | 96.8944 | 50651 |
| LR | 2450 | 81 | 96.7997 | 2531 |
| PK | 4811 | 161 | 96.7619 | 4972 |
| ID | 2232 | 75 | 96.749 | 2307 |
| NP | 831 | 28 | 96.7404 | 859 |
| KE | 26070 | 1001 | 96.3023 | 27071 |
| ZW | 349 | 15 | 95.8791 | 364 |
| GT | 2191 | 95 | 95.8443 | 2286 |
| KH | 22730 | 1032 | 95.6569 | 23762 |
| MD | 227 | 11 | 95.3782 | 238 |
| NG | 5842 | 296 | 95.1776 | 6138 |
| CR | 1425 | 74 | 95.0634 | 1499 |
| US | 460 | 24 | 95.0413 | 484 |
| SL | 3883 | 207 | 94.9389 | 4090 |
| MN | 4381 | 236 | 94.8885 | 4617 |
| BJ | 3225 | 175 | 94.8529 | 3400 |
| SN | 4502 | 248 | 94.7789 | 4750 |
| BI | 285 | 16 | 94.6844 | 301 |
| NI | 15924 | 923 | 94.5213 | 16847 |
| WS | 3974 | 238 | 94.3495 | 4212 |
| BO | 7811 | 469 | 94.3357 | 8280 |
| LB | 4816 | 290 | 94.3204 | 5106 |
| AF | 1613 | 98 | 94.2724 | 1711 |
| EC | 9379 | 602 | 93.9685 | 9981 |
| ML | 2921 | 196 | 93.7119 | 3117 |
| CM | 895 | 62 | 93.5214 | 957 |
| PS | 1692 | 119 | 93.429 | 1811 |
| IN | 141 | 10 | 93.3775 | 151 |
| AZ | 4649 | 333 | 93.3159 | 4982 |
| UG | 11099 | 837 | 92.9876 | 11936 |
| LK | 188 | 15 | 92.6108 | 203 |
| HN | 3442 | 293 | 92.1553 | 3735 |
| TJ | 10468 | 915 | 91.9617 | 11383 |
| SV | 7341 | 642 | 91.9579 | 7983 |
| YE | 399 | 36 | 91.7241 | 435 |
| TZ | 6065 | 580 | 91.2716 | 6645 |
| GE | 1055 | 101 | 91.263 | 1156 |
| BF | 207 | 20 | 91.1894 | 227 |
| TD | 40 | 4 | 90.9091 | 44 |
| XK | 138 | 15 | 90.1961 | 153 |
| AL | 164 | 22 | 88.172 | 186 |
| CO | 3420 | 462 | 88.0989 | 3882 |
| AM | 1251 | 173 | 87.8511 | 1424 |
| IQ | 1008 | 151 | 86.9715 | 1159 |
| ZM | 29 | 8 | 78.3784 | 37 |
| JO | 1817 | 878 | 67.4212 | 2695 |
| BD | 0 | 12 | 0 | 12 |

Appendix 4

List of loans and proportion of funded loans by activity

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Activity** | **Not funded** | **Funded** | **% Funded** | **Total** |
| Bookbinding | 0 | 13 | 100 | 13 |
| Film | 0 | 8 | 100 | 8 |
| Machine Shop | 0 | 64 | 100 | 64 |
| Renewable Energy Products | 0 | 27 | 100 | 27 |
| Well digging | 0 | 29 | 100 | 29 |
| Land Rental | 1 | 79 | 98.75 | 80 |
| Secretarial Services | 2 | 156 | 98.73418 | 158 |
| Weaving | 28 | 1949 | 98.58371 | 1977 |
| Bicycle Sales | 1 | 68 | 98.55072 | 69 |
| Internet Cafe | 8 | 537 | 98.53211 | 545 |
| Musical Performance | 2 | 126 | 98.4375 | 128 |
| Souvenir Sales | 3 | 174 | 98.30508 | 177 |
| Call Center | 4 | 231 | 98.29787 | 235 |
| Metal Shop | 12 | 678 | 98.26087 | 690 |
| Child Care | 2 | 108 | 98.18182 | 110 |
| Tourism | 2 | 103 | 98.09524 | 105 |
| Timber Sales | 11 | 547 | 98.02867 | 558 |
| Primary/secondary school costs | 25 | 1224 | 97.9984 | 1249 |
| Bicycle Repair | 5 | 243 | 97.98387 | 248 |
| Entertainment | 5 | 238 | 97.94239 | 243 |
| Blacksmith | 10 | 456 | 97.85408 | 466 |
| Manufacturing | 40 | 1796 | 97.82135 | 1836 |
| Natural Medicines | 13 | 582 | 97.81513 | 595 |
| Recycled Materials | 5 | 216 | 97.73756 | 221 |
| Embroidery | 21 | 904 | 97.72973 | 925 |
| Furniture Making | 38 | 1607 | 97.68997 | 1645 |
| Knitting | 10 | 412 | 97.63033 | 422 |
| Construction | 54 | 2223 | 97.62846 | 2277 |
| Pharmacy | 31 | 1272 | 97.62087 | 1303 |
| Crafts | 70 | 2864 | 97.61418 | 2934 |
| Traveling Sales | 12 | 483 | 97.57576 | 495 |
| Musical Instruments | 2 | 79 | 97.53086 | 81 |
| Bookstore | 12 | 472 | 97.52066 | 484 |
| Dairy | 93 | 3609 | 97.48784 | 3702 |
| Arts | 13 | 497 | 97.45098 | 510 |
| Phone Repair | 3 | 113 | 97.41379 | 116 |
| Water Distribution | 8 | 301 | 97.411 | 309 |
| Bricks | 13 | 484 | 97.38431 | 497 |
| Hotel | 6 | 223 | 97.37991 | 229 |
| Education provider | 12 | 433 | 97.30337 | 445 |
| Dental | 3 | 108 | 97.2973 | 111 |
| Higher education costs | 33 | 1181 | 97.28171 | 1214 |
| Carpentry | 31 | 1109 | 97.2807 | 1140 |
| Cheese Making | 7 | 242 | 97.18876 | 249 |
| Laundry | 7 | 242 | 97.18876 | 249 |
| Printing | 10 | 341 | 97.151 | 351 |
| Recycling | 14 | 471 | 97.1134 | 485 |
| Medical Clinic | 8 | 266 | 97.08029 | 274 |
| Computers | 13 | 432 | 97.07865 | 445 |
| Bakery | 95 | 3014 | 96.94436 | 3109 |
| Patchwork | 2 | 63 | 96.92308 | 65 |
| Fishing | 82 | 2497 | 96.82047 | 2579 |
| Fish Selling | 205 | 6224 | 96.81132 | 6429 |
| Cloth & Dressmaking Supplies | 53 | 1579 | 96.75245 | 1632 |
| Cobbler | 17 | 504 | 96.73704 | 521 |
| Goods Distribution | 18 | 533 | 96.73321 | 551 |
| Motorcycle Repair | 12 | 353 | 96.71233 | 365 |
| Games | 8 | 235 | 96.70782 | 243 |
| Textiles | 21 | 613 | 96.6877 | 634 |
| Photography | 14 | 407 | 96.67458 | 421 |
| Catering | 49 | 1413 | 96.64843 | 1462 |
| Sewing | 132 | 3794 | 96.6378 | 3926 |
| Fuel/Firewood | 57 | 1625 | 96.61118 | 1682 |
| Food Production/Sales | 627 | 17426 | 96.52689 | 18053 |
| Pigs | 257 | 7024 | 96.47027 | 7281 |
| Tailoring | 153 | 4141 | 96.43689 | 4294 |
| Balut-Making | 1 | 27 | 96.42857 | 28 |
| Fruits & Vegetables | 350 | 8983 | 96.24987 | 9333 |
| Motorcycle Transport | 185 | 4744 | 96.2467 | 4929 |
| Cereals | 110 | 2809 | 96.23159 | 2919 |
| Charcoal Sales | 131 | 3275 | 96.15385 | 3406 |
| Religious Articles | 4 | 99 | 96.1165 | 103 |
| Milk Sales | 31 | 766 | 96.11041 | 797 |
| Jewelry | 38 | 921 | 96.03754 | 959 |
| Used Clothing | 149 | 3557 | 95.97949 | 3706 |
| Waste Management | 4 | 95 | 95.9596 | 99 |
| Restaurant | 165 | 3900 | 95.94096 | 4065 |
| Poultry | 144 | 3403 | 95.94023 | 3547 |
| Food Market | 416 | 9814 | 95.93353 | 10230 |
| General Store | 1103 | 25464 | 95.84823 | 26567 |
| Phone Use Sales | 15 | 345 | 95.83333 | 360 |
| Butcher Shop | 87 | 1953 | 95.73529 | 2040 |
| Agriculture | 609 | 13372 | 95.64409 | 13981 |
| Grocery Store | 605 | 13087 | 95.58136 | 13692 |
| Used Shoes | 10 | 215 | 95.55556 | 225 |
| Office Supplies | 16 | 342 | 95.53073 | 358 |
| Personal Medical Expenses | 11 | 232 | 95.47325 | 243 |
| Quarrying | 11 | 232 | 95.47325 | 243 |
| Transportation | 132 | 2783 | 95.4717 | 2915 |
| Health | 13 | 274 | 95.47038 | 287 |
| Food Stall | 218 | 4587 | 95.46306 | 4805 |
| Construction Supplies | 83 | 1714 | 95.38119 | 1797 |
| Electrician | 12 | 247 | 95.3668 | 259 |
| Liquor Store / Off-License | 45 | 924 | 95.35604 | 969 |
| Rickshaw | 25 | 513 | 95.35316 | 538 |
| Perfumes | 14 | 284 | 95.30201 | 298 |
| Beauty Salon | 205 | 4142 | 95.2841 | 4347 |
| Barber Shop | 40 | 808 | 95.28302 | 848 |
| Flowers | 17 | 333 | 95.14286 | 350 |
| Property | 43 | 840 | 95.13024 | 883 |
| Wholesale | 14 | 272 | 95.1049 | 286 |
| Shoe Sales | 139 | 2663 | 95.03926 | 2802 |
| Hardware | 39 | 734 | 94.95472 | 773 |
| Soft Drinks | 115 | 2129 | 94.87522 | 2244 |
| Electronics Repair | 22 | 407 | 94.87179 | 429 |
| Sporting Good Sales | 2 | 37 | 94.87179 | 39 |
| Farming | 1249 | 22978 | 94.84459 | 24227 |
| Utilities | 9 | 165 | 94.82759 | 174 |
| Animal Sales | 322 | 5842 | 94.77612 | 6164 |
| Veterinary Sales | 6 | 106 | 94.64286 | 112 |
| Plastics Sales | 30 | 529 | 94.63327 | 559 |
| Cement | 8 | 140 | 94.59459 | 148 |
| Pub | 48 | 834 | 94.55782 | 882 |
| Clothing | 81 | 1368 | 94.40994 | 1449 |
| Clothing Sales | 1036 | 17477 | 94.40393 | 18513 |
| Decorations Sales | 18 | 301 | 94.35737 | 319 |
| Vehicle | 82 | 1370 | 94.35262 | 1452 |
| Livestock | 269 | 4399 | 94.23736 | 4668 |
| Retail | 1417 | 22753 | 94.13736 | 24170 |
| Movie Tapes & DVDs | 19 | 296 | 93.96825 | 315 |
| Cosmetics Sales | 261 | 4052 | 93.94853 | 4313 |
| Music Discs & Tapes | 10 | 154 | 93.90244 | 164 |
| Spare Parts | 83 | 1276 | 93.89257 | 1359 |
| Services | 329 | 5054 | 93.88817 | 5383 |
| Personal Products Sales | 92 | 1383 | 93.76271 | 1475 |
| Auto Repair | 82 | 1226 | 93.73089 | 1308 |
| Electronics Sales | 38 | 567 | 93.71901 | 605 |
| Cattle | 301 | 4446 | 93.65915 | 4747 |
| Vehicle Repairs | 57 | 823 | 93.52273 | 880 |
| Food | 251 | 3624 | 93.52258 | 3875 |
| Upholstery | 7 | 101 | 93.51852 | 108 |
| Home Energy | 13 | 180 | 93.26425 | 193 |
| Cafe | 103 | 1421 | 93.24147 | 1524 |
| Home Products Sales | 253 | 3461 | 93.18794 | 3714 |
| Paper Sales | 30 | 380 | 92.68293 | 410 |
| Farm Supplies | 151 | 1868 | 92.52105 | 2019 |
| Personal Purchases | 81 | 999 | 92.5 | 1080 |
| Mobile Phones | 45 | 534 | 92.22798 | 579 |
| Electrical Goods | 31 | 365 | 92.17172 | 396 |
| Taxi | 257 | 3024 | 92.16702 | 3281 |
| Phone Accessories | 38 | 386 | 91.03774 | 424 |
| Consumer Goods | 16 | 147 | 90.18405 | 163 |
| Air Conditioning | 5 | 41 | 89.13043 | 46 |
| Party Supplies | 17 | 134 | 88.74172 | 151 |
| Home Appliances | 35 | 268 | 88.44884 | 303 |
| Personal Housing Expenses | 1132 | 8207 | 87.87879 | 9339 |
| Funeral Expenses | 1 | 7 | 87.5 | 8 |
| Machinery Rental | 9 | 56 | 86.15385 | 65 |
| Wedding Expenses | 20 | 103 | 83.73984 | 123 |