Document Classification Case Study: Kiva Loans

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1 Introduction

Kiva Microfunds is a non-profit that allows people to lend money to low-income entrepreneurs and students around the world. Started in 2005, Kiva has crowd-funded millions of loans with a repayment rate of 98% to 99%.

In additional to traditional demographic data, Kiva includes personal stories on each borrower because they want lenders to connect with the borrowers on a human level. An example:

Evelyn is 40 years old and married with 3 kids. She is in the Karura Hope women group and her life has been changed by the first KIVA loan she received last year which she is completing this quarter. Before she received the loan, she used to sell 9 litres of milk daily to local residents. After receiving the loan she bought iron sheets, five cement packets, one lorry of sand, some ballast and animal feed for her cows and improved her cow shed. Today she sells a daily average of 40 litres of milk to the Kiamba Dairy cooperative society, which is affiliated to the Kenya Cooperative Creameries at a cost of USD 0.28 per litre. Her daily farming has really grown. Evelyn intends to buy another dairy cow and a tank of water for home consumption and for her cows. She intends to repay in monthly installments.

Despite her uplifting story, and her previous successful loan, Evelyn defaulted on her next loan of 900 USD.

In this case study, we will explore past Kiva loans and build a prediction model (in particular, a decision tree classifier) to predict which future borrowers will pay back loans, and which will default. A key question we will explore is: does adding text (i.e., the personal stories) to the prediction model increase or decrease its prediction power?

This case study will provide lots of data and graphs, but is intentionally light on commentary, analysis, and decision making. That's your job!

1.1 Case Discussion Questions

At the end of this case study, we will have a group discussion around the following questions:

1. Does text data help in predicting which loan seeker will default?
2. Which words are most biased towards defaulting? Is this expected/intuitive?
3. According to the decision tree prediction models, what variables best predict a default?
4. As a decision maker, would you recommend the use of textual data in your prediction models?

2 Kiva Background

The key terms in the Kiva world are:

- **The loan**. A loan is the most important data object at Kiva. Most other objects are in some way related to a loan.
- **The borrower**. A borrower is someone who has requested a loan. Borrowers are often referred to as "businesses or"entrepreneurs" in order to emphasize the entrepreneurial spirit of these individuals who work to make a difference in their lives.
- **The lender**. A lender is a user registered on the Kiva website for the purposes of lending money and participating in the community. Some lenders have public profiles, known as lender pages, on the Kiva website, where they can share details about their activities and mission. Most lenders, however, refrain from displaying their public information and are referred to as "anonymous."
- **The partner.** A partner, or Kiva field partner, is usually a microfinance institution with which Kiva works to find and fund loans. Every loan at Kiva is offered by a partner to a borrower, and the partner works with Kiva to get funding for that loan from lenders.

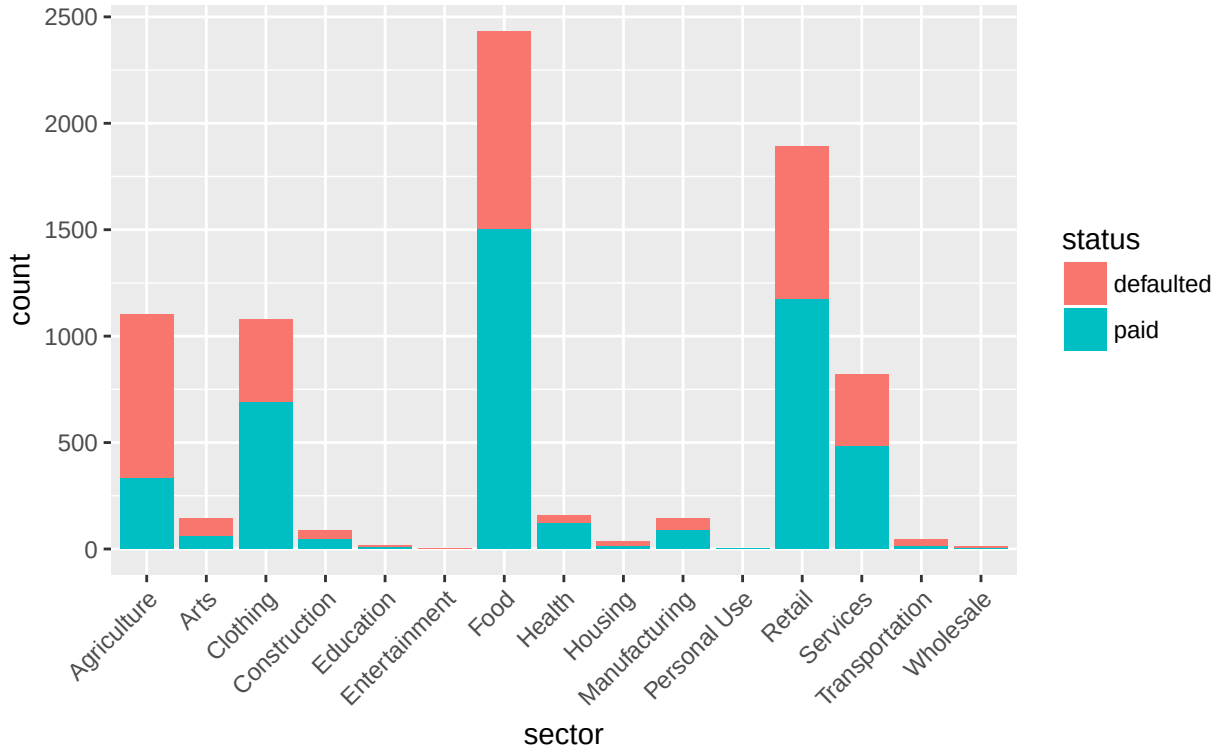
3 Data Description

The data is collected from build.kiva, Kiva's website for providing snapshots of their data from time to time. In the full dataset, about 98% of loans are repaid and 2% defaulted. In this case study, we look at only a sample of the data, where the split between repaid and defaulted is closer to 50%-50%.

Let's look at our sample to understand the size, shape, values, and patterns in the variables. The dataset inclues 8 variables, named: status, sector, en, country, gender, loan_amount, nonpayment, id. Most the names of the variables are self-describing. The `en` variable is the text variable, i.e., the personal story of the loan seeker, and will be our main source of investigation. There are 7988 records/rows/loans in our sample.

3.1 Variable: sector

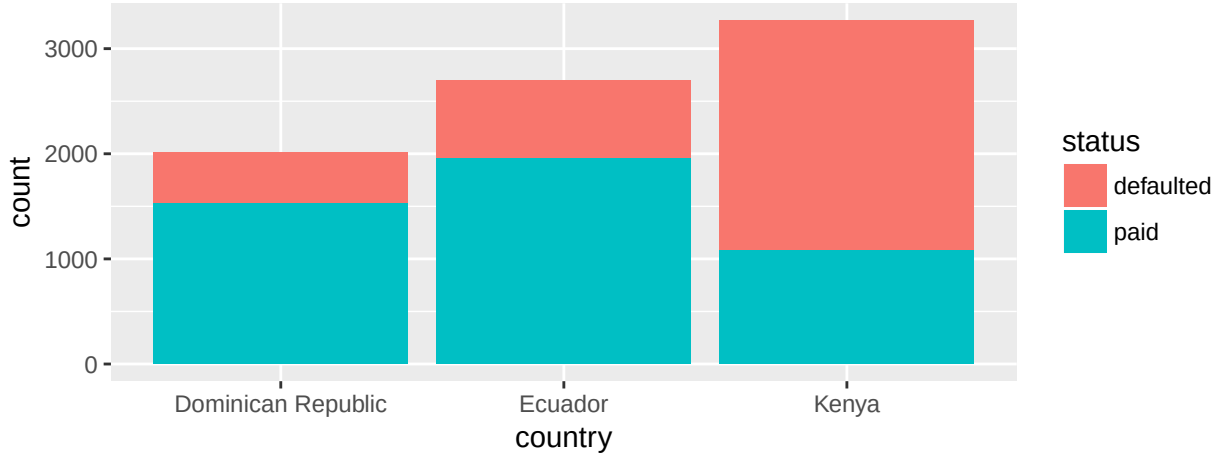
The first variable in the dataset is `sector`. Let's look at how many loans are in each sector, and tabulate how many have paid and how many have defaulted.



sector	defaulted	paid	total
Agriculture	769	335	1104
Arts	81	63	144
Clothing	386	694	1080
Construction	42	47	89
Education	5	13	18
Entertainment	2	2	4
Food	927	1505	2432
Health	33	123	156
Housing	23	12	35
Manufacturing	52	92	144
Personal Use	NA	3	NA
Retail	718	1177	1895
Services	337	485	822
Transportation	31	17	48
Wholesale	5	9	14

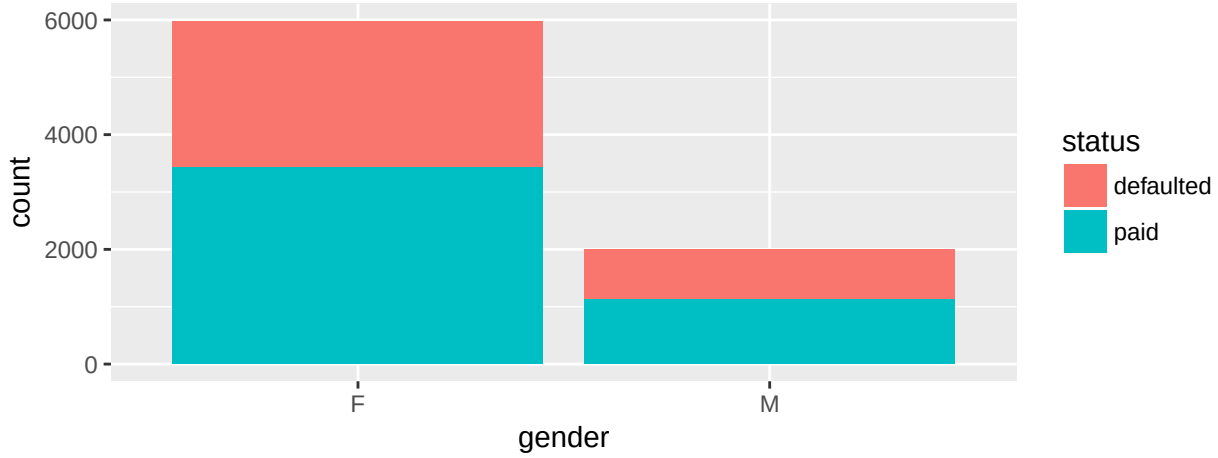
3.2 Variable: country

Let's do the same for the `country` variable: cross tabulation table, and a graphical representation.



country	defaulted	paid	total
Dominican Republic	485	1533	2018
Ecuador	739	1963	2702
Kenya	2187	1081	3268

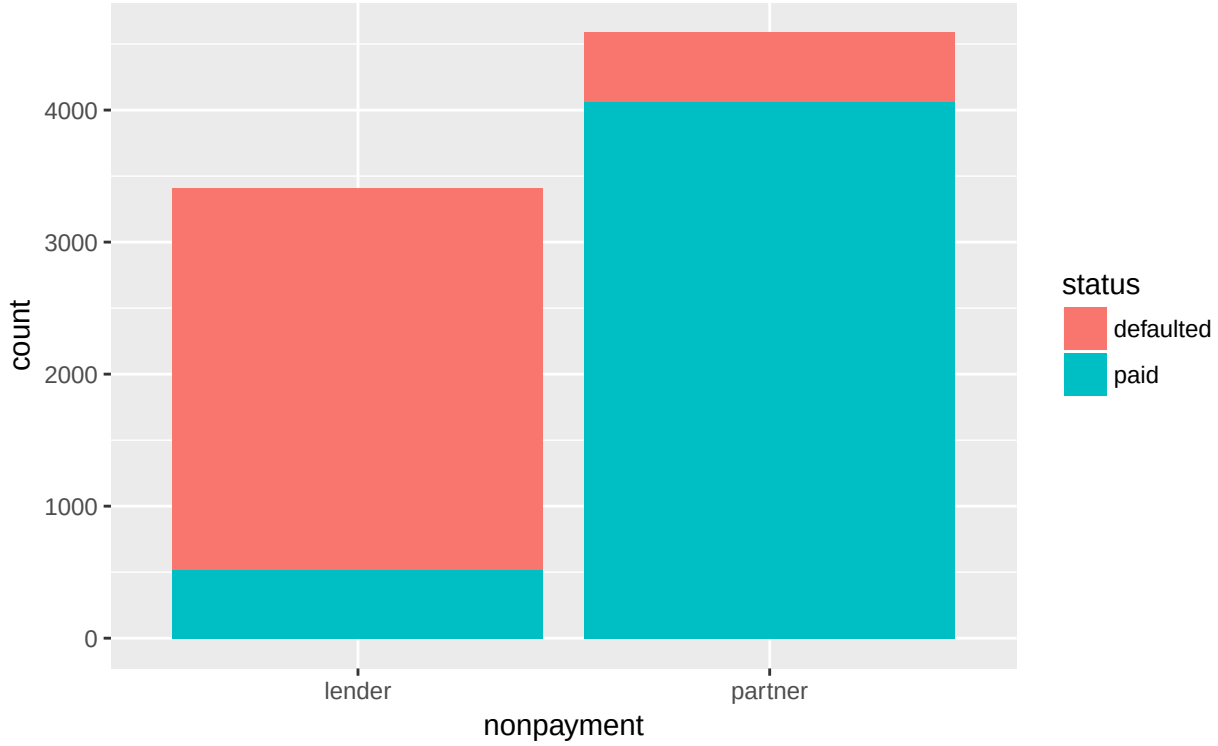
3.3 Variable: gender



gender	defaulted	paid	total
F	2541	3445	5986
M	870	1132	2002

3.4 Variable: nonpayment

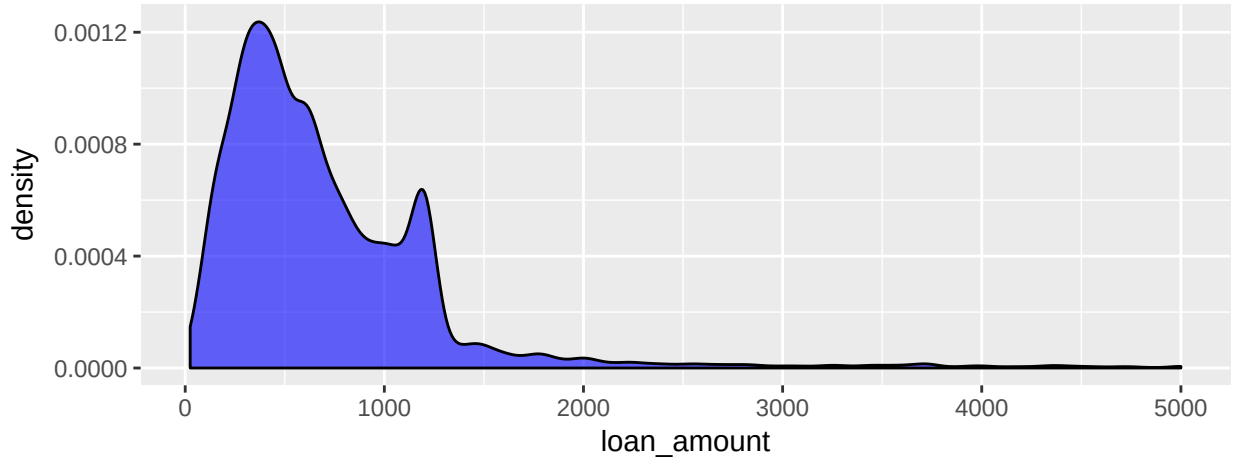
The nonpayment variable captures who is liable if a loan defaults: the lender, or the partner.



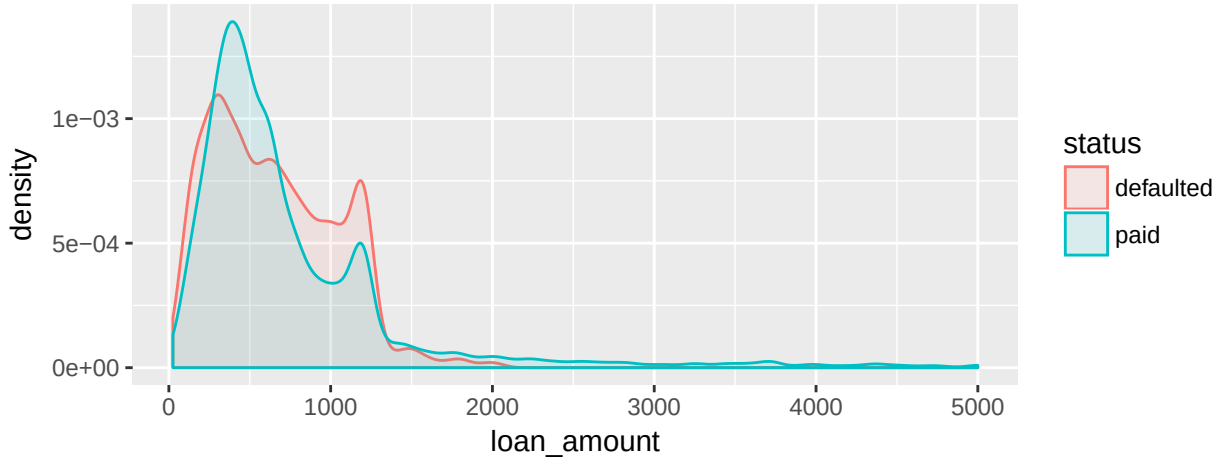
nonpayment	defaulted	paid	total
lender	2887	516	3403
partner	524	4061	4585

3.5 Variable: loan_amount

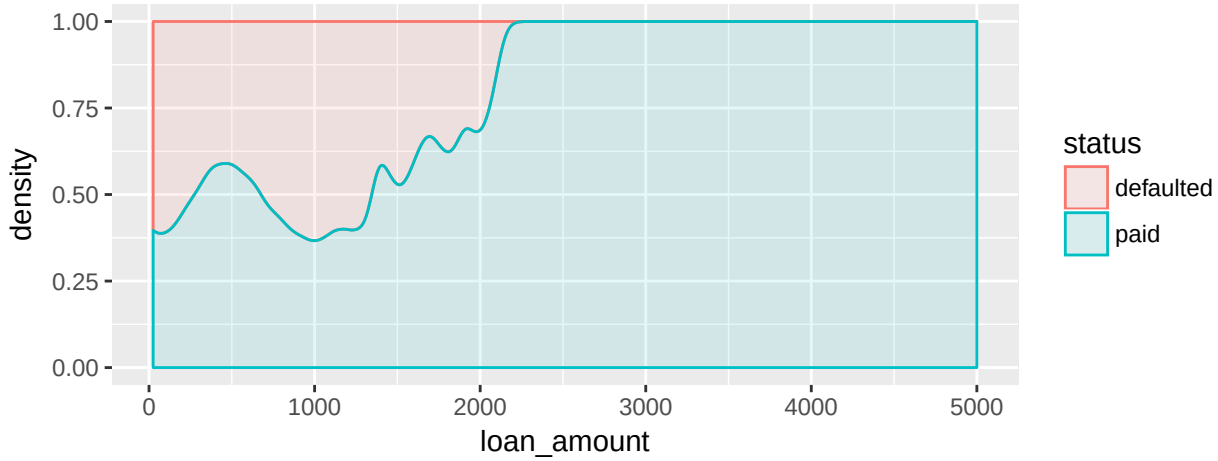
Since the `loan_amount` variable is numeric, we can look at a density plot.



We can show a separate density for `status=defaulted` and `status=paid`.



And we can even show a "filled" density plot:

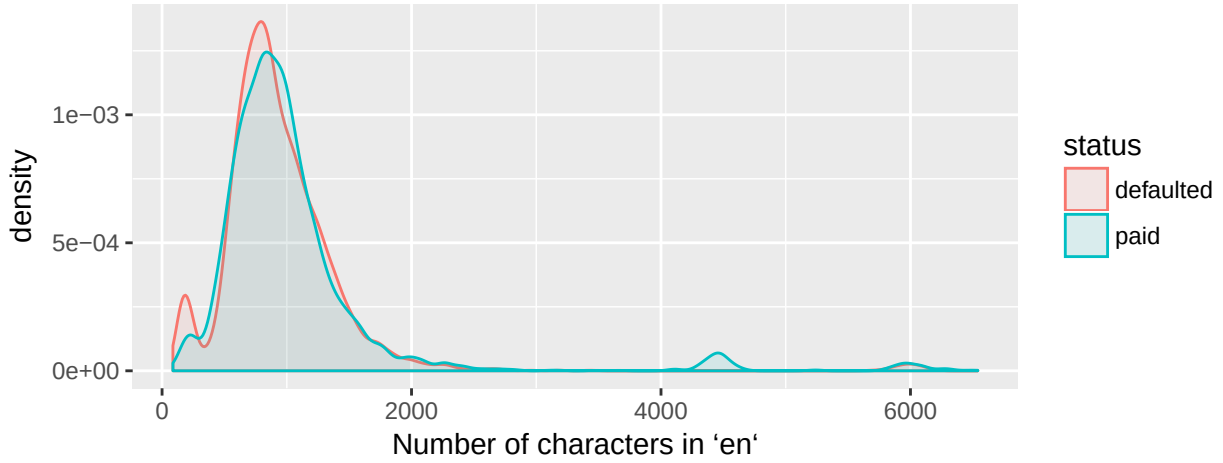


3.6 Variable: en

The `en` variable is raw English text, and there's lots of ways we can look at it.

3.6.1 Length

First, let's look at a density plot of the length (number of characters/letters).



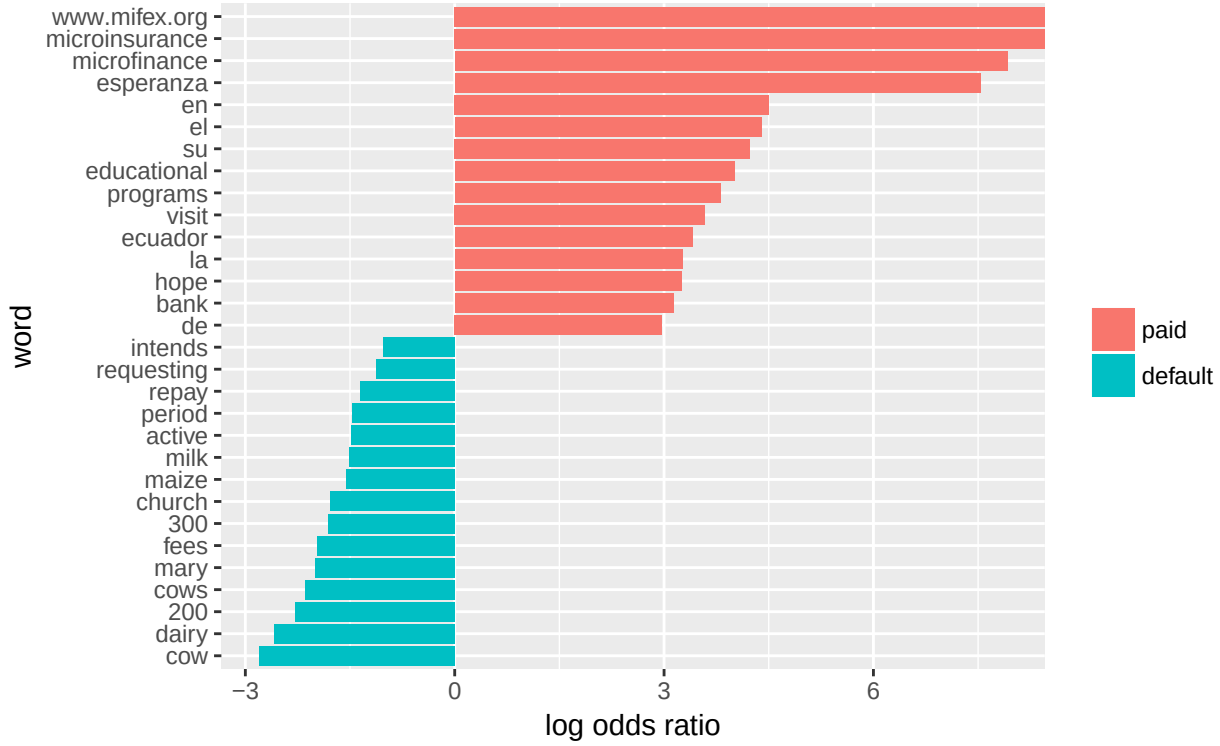
3.6.2 Top Words

Let's look at the top (i.e, most frequent) words.

word	count	freq
children	8634	0.0151617
school	5124	0.0089980
buy	4963	0.0087153
sells	3957	0.0069487
family	3764	0.0066098
products	3289	0.0057756
husband	3273	0.0057475
income	3203	0.0056246
married	3081	0.0054104
selling	2979	0.0052313
home	2954	0.0051874
community	2681	0.0047080
rice	2638	0.0046325
purchase	2605	0.0045745
started	2575	0.0045218
store	2427	0.0042619
clients	2291	0.0040231
increase	2230	0.0039160
house	2176	0.0038212
customers	2170	0.0038106

3.6.3 Most Biased Words

Now, let's see which words are more biased towards being `paid` or `defaulted`, using the log odds ratio metric.



Let's look at a tabular version of the same data above, first focusing on the words that are biased towards `paid`:

word	defaulted	paid	total	log_ratio
microinsurance	0	603	603	Inf
www.mifex.org	0	601	601	Inf
microfinance	3	726	729	7.918863
esperanza	6	1112	1118	7.533979
en	24	544	568	4.502500
el	30	633	663	4.399171
su	41	769	810	4.229288
educational	38	613	651	4.011816
programs	55	771	826	3.809227
visit	62	746	808	3.588836
ecuador	101	1070	1171	3.405184
la	69	663	732	3.264341
hope	52	495	547	3.250845
bank	122	1071	1193	3.134005
de	193	1514	1707	2.971693
lucia	71	541	612	2.929738
access	147	1105	1252	2.910158

And those that are biased towards `default`:

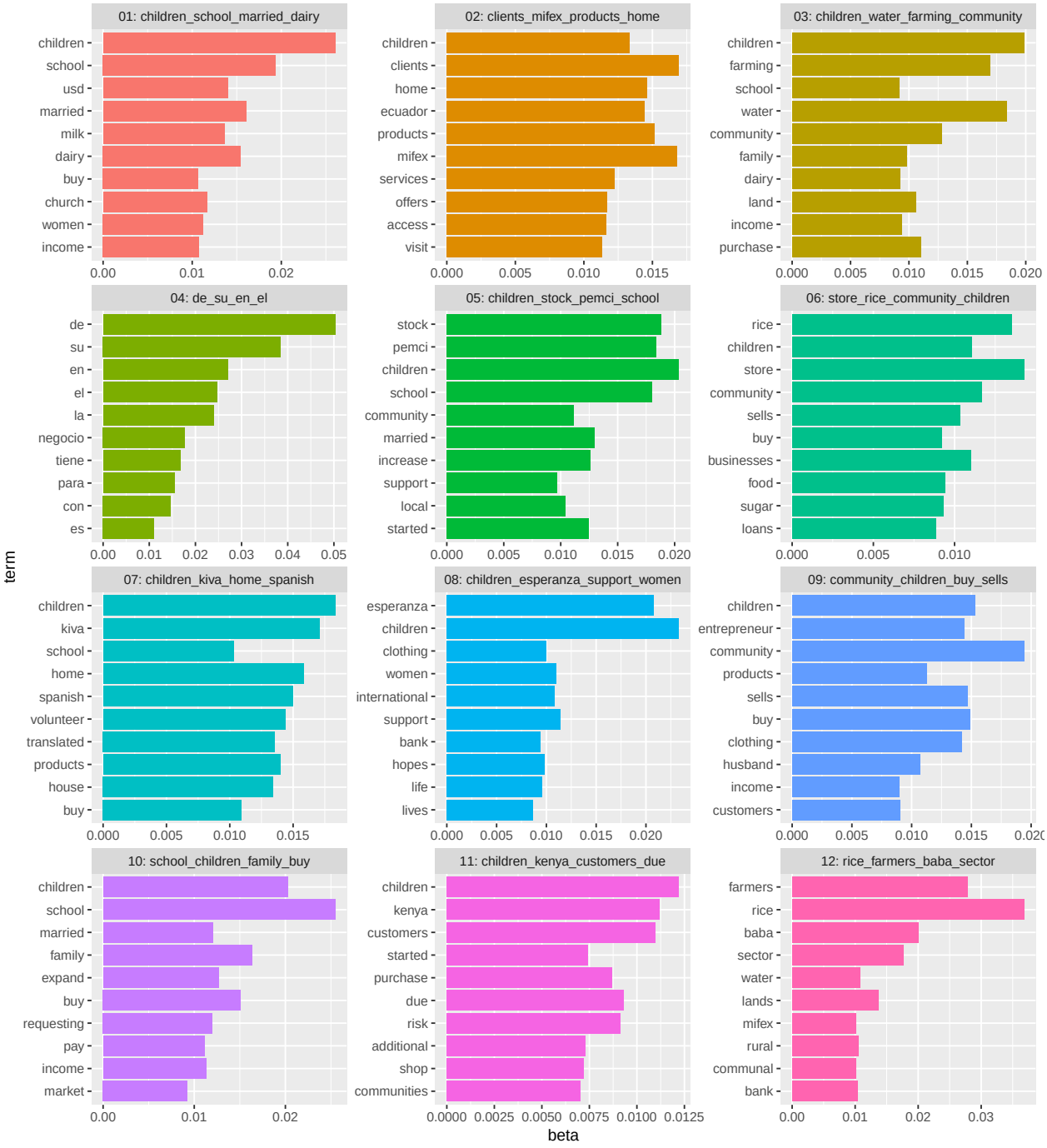
word	defaulted	paid	total	log_ratio
cow	455	65	520	-2.8073549
dairy	914	152	1066	-2.5881228
200	454	93	547	-2.2873897
cows	414	94	508	-2.1388981
mary	412	103	515	-2.0000000
fees	687	176	863	-1.9647347
300	394	112	506	-1.8146969
church	561	163	724	-1.7831288
maize	480	163	643	-1.5581624
milk	767	270	1037	-1.5062672
active	504	180	684	-1.4854268
period	404	146	550	-1.4683869
repay	1003	391	1394	-1.3590811
requesting	944	433	1377	-1.1244198
intends	456	224	680	-1.0255351
100	530	266	796	-0.9945661
personal	432	232	664	-0.8969065
farming	676	385	1061	-0.8121648
usd	623	355	978	-0.8114131
12	394	236	630	-0.7394088

3.7 LDA Topics

We used a techinque called Latent Dirichlet Allocation (LDA) to automatically uncover the topics from the documents. We told LDA to discover the 12 most important topics in the documents; LDA will also tell us which topics are in which documents.

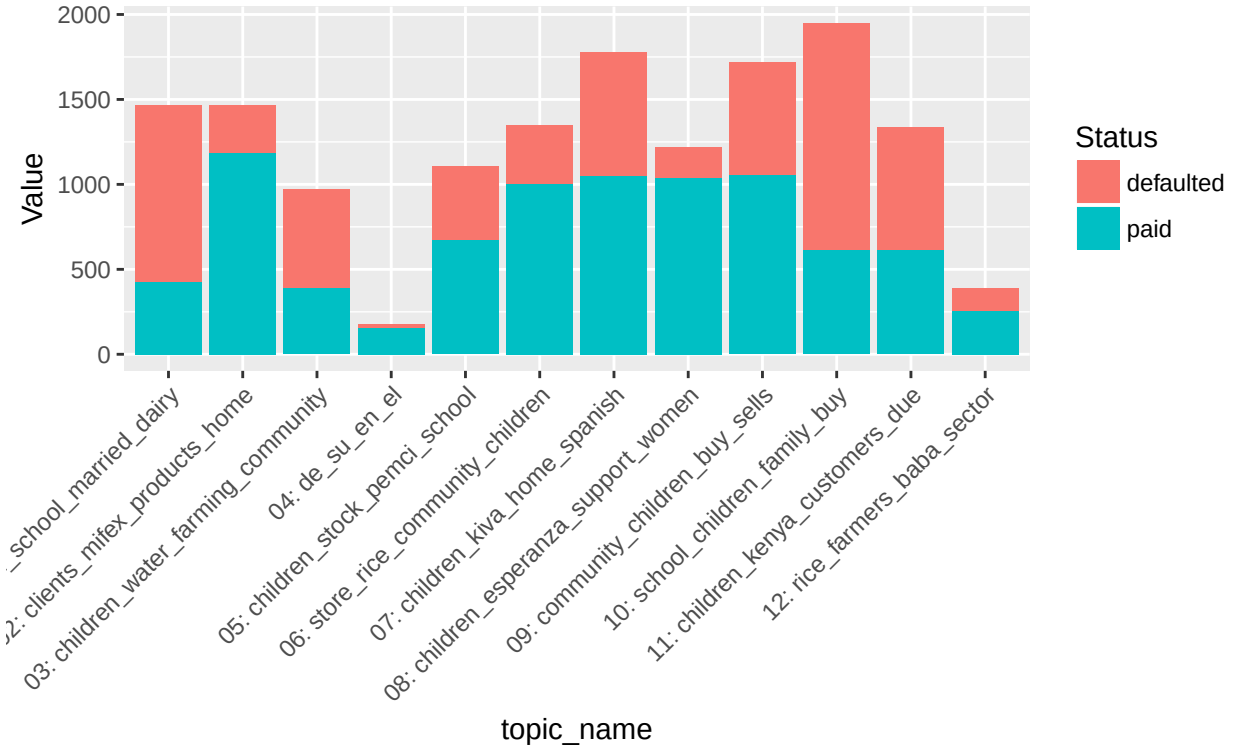
3.7.1 LDA Top Terms Per Topic

First, let's look at the top terms (words) in each discovered topic.



3.7.2 Documents per LDA Topic

Next, let's look at how many documents have each topic.



topic	topic_name	defaulted	paid	total
1	01: children_school_married_dairy	1041	424	1465
2	02: clients_mifex_products_home	279	1189	1468
3	03: children_water_farming_community	581	388	969
4	04: de_su_en_el	23	153	176
5	05: children_stock_pemci_school	430	676	1106
6	06: store_rice_community_children	343	1007	1350
7	07: children_kiva_home_spanish	724	1050	1774
8	08: children_esperanza_support_women	179	1038	1217
9	09: community_children_buy_sells	660	1059	1719
10	10: school_children_family_buy	1332	617	1949
11	11: children_kenya_customers_due	718	616	1334
12	12: rice_farmers_baba_sector	131	254	385

4 Building a Classifier Model

Now that we have explored the data, it's time to dive deeper. Which variable(s) are the biggest predictors of `status`? This is where classifier models shine. They can tell us exactly how all the variables relate to each other, and which are most important.

A decision tree is a popular classifier model in analytics. Here, the decision tree is automatically created by a machine learning algorithm as it learns simple decision rules from the data. These automatically-learned rules can then be used to both understand the variables and to predict future data. A big advantage of decision trees over other classifier models is that they are relatively simple for humans to understand and interpret.

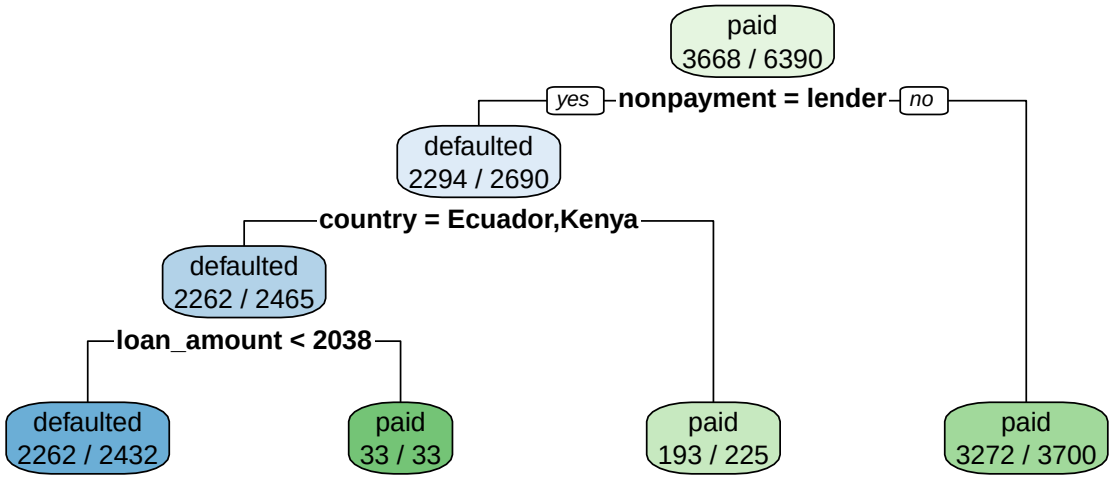
A decision tree consists of nodes. Each node splits the data according to a rule. A rule is based on a variable in the data. For example, a rule might be "Age greater than 30." In this case, the node splits the data by the age variable; those passengers that satisfy the rule (i.e., are greater than 30) follow the left path out of the node; the rest follow the right path out of the node. In this way, paths from the root node down to leaf nodes are created, describing the fate of certain types of passengers.

A decision tree path always starts with a root node (node number 1), which contains the most important splitting rule. Each subsequent node contains the next most important rule. After the decision tree is automatically created by the machine learning algorithm, one can use the decision tree to classify an individual by simply following a path: start at the root node and apply each rule to follow the appropriate path until you hit an end.

When creating a decision tree from data, the analyst can specify the number of nodes for the machine learning algorithm to create. More nodes leads to a more accurate model, at the cost of a more complicated and harder-to-interpret model. Likewise, fewer nodes usually leads to a less accurate model, but the model is easier to understand and interpret.

5 A Prediction Model without the Text

First, as a baseline, let's train a decision tree classifier model without using any of the text or topics. Here is a graphical depiction of the model after it has been trained:



Now, let's see how accurate the model is. We'll use some never-before-seen data (called *testing data*). We'll give the testing data to the classifier, ask it to make a prediction (i.e., whether the borrower will pay or not), and then we'll see if the classifier is correct.

The following table summarizes the predictions of the classifier.

predicted	actual	Freq
defaulted	defaulted	50
paid	defaulted	39
defaulted	paid	24
paid	paid	120

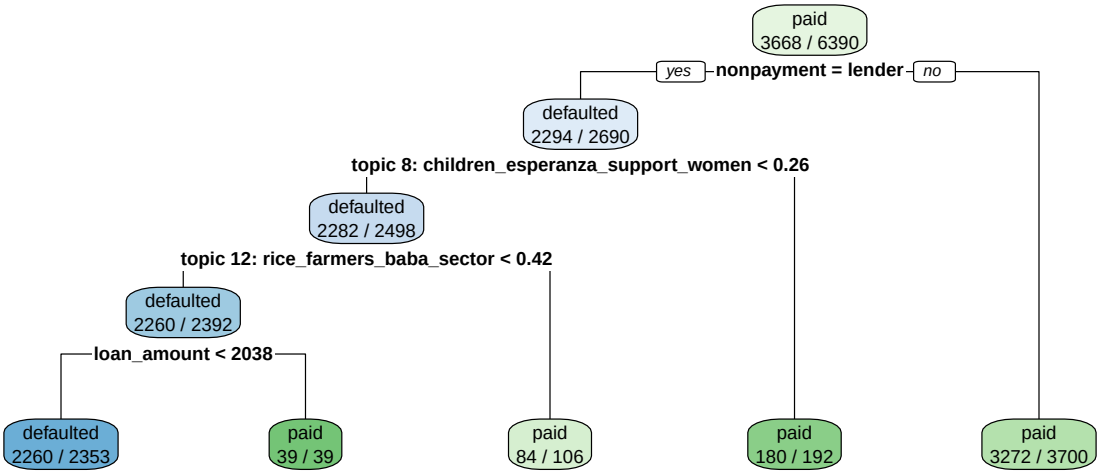
That is, the model predicted `defaulted` 50 times correctly, and 24 times incorrectly. It also predicted `paid` correctly 120 times, and 39 times incorrectly.

Let's check the accuracy and other metrics of the classifier on the testing data.

```
## [1] "Accuracy:    0.730"

## [1] "Precision:   0.676"

## [1] "Recall:      0.562"

## [1] "F1 Score:    0.613"

## [1] "Sensitivity: 0.562"

## [1] "Specificity: 0.755"
```

6 A Prediction Model with the Text

Now, let's build the same decision tree classifier model as before, except now, let's include the LDA topics, which were built from the text. (Note: there are many *other* textual features we could include in this model: individual words, clusters, etc. However, we'll keep it simple for now.)



Confusion matrix:

predicted	actual	Freq
defaulted	defaulted	573
paid	defaulted	106
defaulted	paid	35
paid	paid	556

Metrics:

```
## [1] "Accuracy:    0.889"
## [1] "Precision:   0.942"
## [1] "Recall:      0.844"
## [1] "F1 Score:    0.890"
## [1] "Sensitivity: 0.844"
## [1] "Specificity: 0.840"
```

7 Appendix: Further Reading

- Kiva.org. Kiva's homepage.
- Build.Kiva. Kiva data dumps and data description.