LendingClub

Predicting Loan Defaults

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Outline

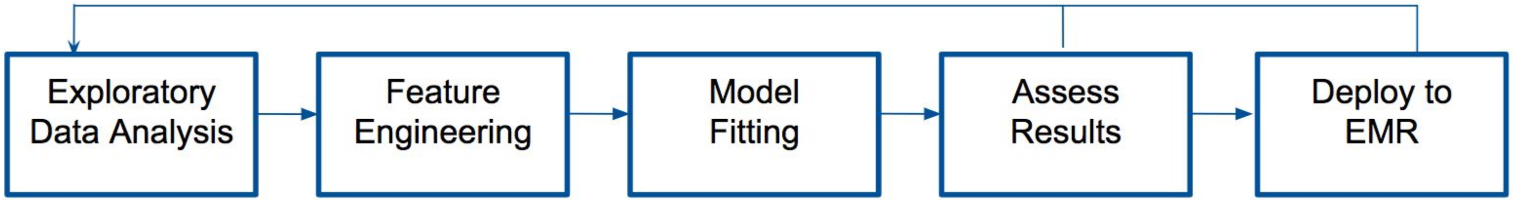
- Data & Introduction
- Feature Engineering
- Modeling
- Results and Evaluation
- Lessons Learned

LendingClub

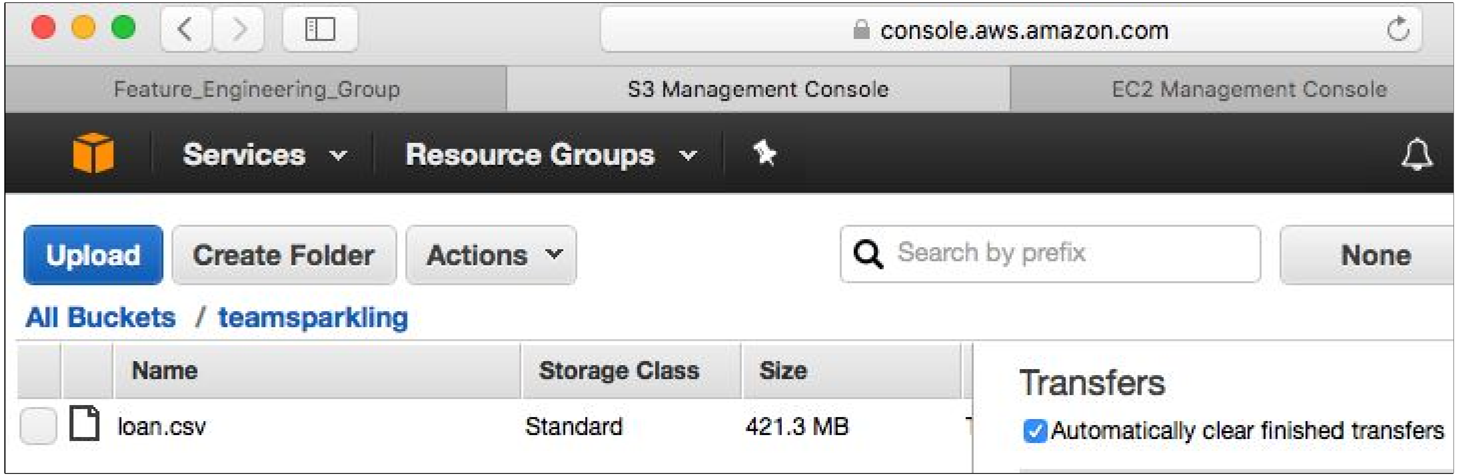
Data & Introduction

- Analytics goal
  - **Predict whether a customer will pay off the loan**
- Why we chose this data:
  - Interesting and challenging: 73 total features, 880,000 observations
  - Successful predictions increase profit for investors

Data processing



Data in S3 Bucket



Create Data Frame & Spark SQL

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jupyter Feature_Engineering_Group (unsaved changes)

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Code CellToolbar

1. Import Libraries

In [1]:
```
from pyspark.sql.types import *
from pyspark.ml.feature import StringIndexer, OneHotEncoder
from pyspark.sql.functions import *
```

2. Load Data and Convert to Spark Data Frame

In [2]:
```
# load data as dataframe
loan_df = spark.read.csv("s3n://teamsparkling/loan.csv", header=True)
```

In [3]:
```
loan_df.rdd.getNumPartitions()
```

Out[3]: 64

```
loan_df_final.select('paid_flag',
     'loan_amnt',
     'funded_amnt',
     'int_rate',
     'installment',
     'annual_inc').show(10)
```

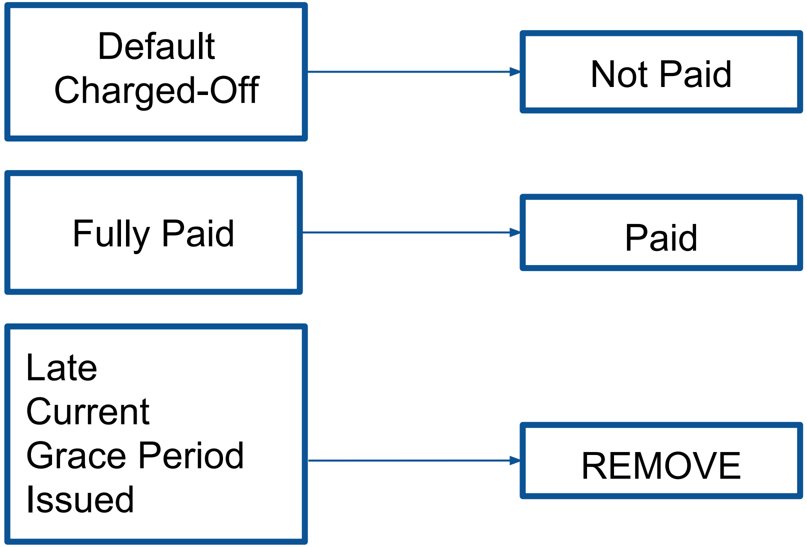
paid_flag	loan_amnt	funded_amnt	int_rate	installment	annual_inc
0	5000.0	5000.0	10.65	162.87	24000.0
1	2500.0	2500.0	15.27	59.83	30000.0
0	2400.0	2400.0	15.96	84.33	12252.0
0	10000.0	10000.0	13.49	339.31	49200.0
0	5000.0	5000.0	7.9	156.46	36000.0
0	3000.0	3000.0	18.64	109.43	48000.0
1	5600.0	5600.0	21.28	152.39	40000.0
1	5375.0	5375.0	12.69	121.45	15000.0
0	6500.0	6500.0	14.65	153.45	72000.0
0	12000.0	12000.0	12.69	402.54	75000.0

only showing top 10 rows

Feature Engineering

- Create response variable
- Convert data type
- Bucket feature categories
- Encode categorical features
- Handle missing values

Feature Engineering - Response Variable



- *Current* does not imply the loan will be paid
- *Late* does not imply the loan will not be paid

Feature Engineering - Data Cleaning

emp_length
9 years
5 years
1 year
n/a
2 years
7 years
8 years
4 years
6 years
3 years
10+ years
< 1 year

→

emp_len
null
1
6
3
5
9
4
8
7
10
2

```python
import re
def convert_to_int(s):
    s = re.sub('\\D', '', s)  #remove any non-digital character
    #\d matches any digital, #\D matches any non-digital
    try:
        return s
    except ValueError:
        return None

emp_to_num = udf(convert_to_int)
loan_df4 = loan_df3.withColumn('emp_len',emp_to_num('emp_length').cast('integer'))
```

Feature Engineering - Categorical Features

```
+--------------+
|home_ownership|
+--------------+
|           OWN|
|          RENT|
|      MORTGAGE|
|           ANY|
|         OTHER|
|          NONE|
+--------------+
```

re-group

```
+--------------+
|home_ownership|
+--------------+
|           OWN|
|         Other|
|          RENT|
|      MORTGAGE|
+--------------+
```

encode

```
+---------------------+
|home_ownership-onehot|
+---------------------+
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[2],[1.0])|
|      (4,[1],[1.0])|
|      (4,[2],[1.0])|
|      (4,[2],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[0],[1.0])|
|      (4,[0],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
|      (4,[1],[1.0])|
+---------------------+
```

Feature Engineering - Missing Values

3.3.7 deal with missing values

```
# Filling NA values with 0
loan_df8 = loan_df8.fillna(0.0, ['tot_coll_amt','tot_cur_bal', 'total_rev_hi_lim'])
# Drop rows with NA
loan_df9 = loan_df8.dropna()
```

- Filling missing value with 0
- Drop rows with missing value

Logistic Regression & CV parameter tuning

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4.3 Logistic Regression

2]:

```
lr = LogisticRegression()
evaluator = BinaryClassificationEvaluator()

cv = CrossValidator().setEstimator(lr).setEvaluator(evaluator).setNumFolds(5)
paramGrid = ParamGridBuilder().addGrid(lr.maxIter,[100]).addGrid(lr.regParam,[0.1,0.01,0.001,1]).build()

cv.setEstimatorParamMaps(paramGrid)
cvmodel = cv.fit(data_train)
```

4]:

```
predictions = cvmodel.bestModel.transform(data_test)
score = evaluator.evaluate(cvmodel.bestModel.transform(data_test))
print evaluator.getMetricName()+":"+str(score)
```

```
areaUnderROC:0.703155187142
```

Random Forest & CV parameter tuning

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yter Feature_Engineering_Group (autosaved)

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4.2 Random Forest

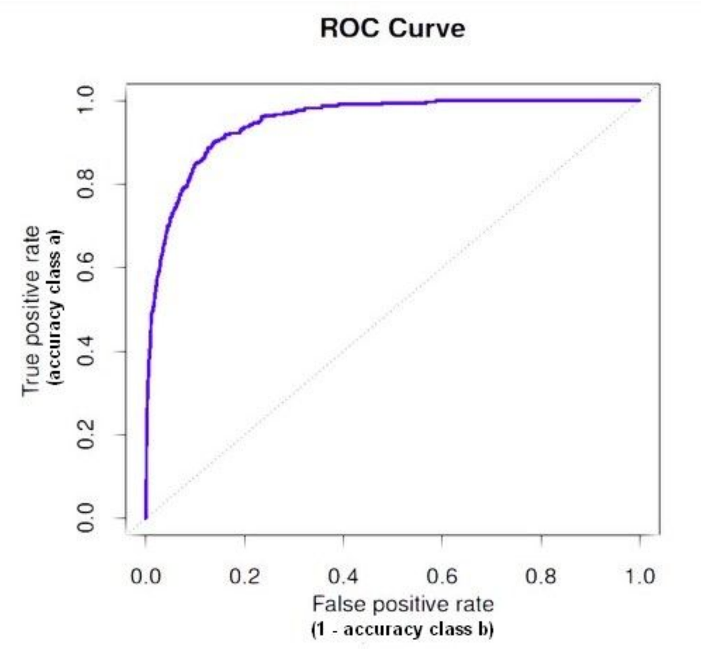
3]:

```
# Fit random forest
rf = RandomForestClassifier()
evaluator_rf = BinaryClassificationEvaluator()
cv = CrossValidator().setEstimator(rf).setEvaluator(evaluator_rf).setNumFolds(5)
paramGrid = ParamGridBuilder().addGrid(rf.numTrees,[31,51]).addGrid(rf.maxDepth,[5,15]).build()

cv.setEstimatorParamMaps(paramGrid)
cvmodel_rf = cv.fit(data_train)
```

Evaluation Metrics

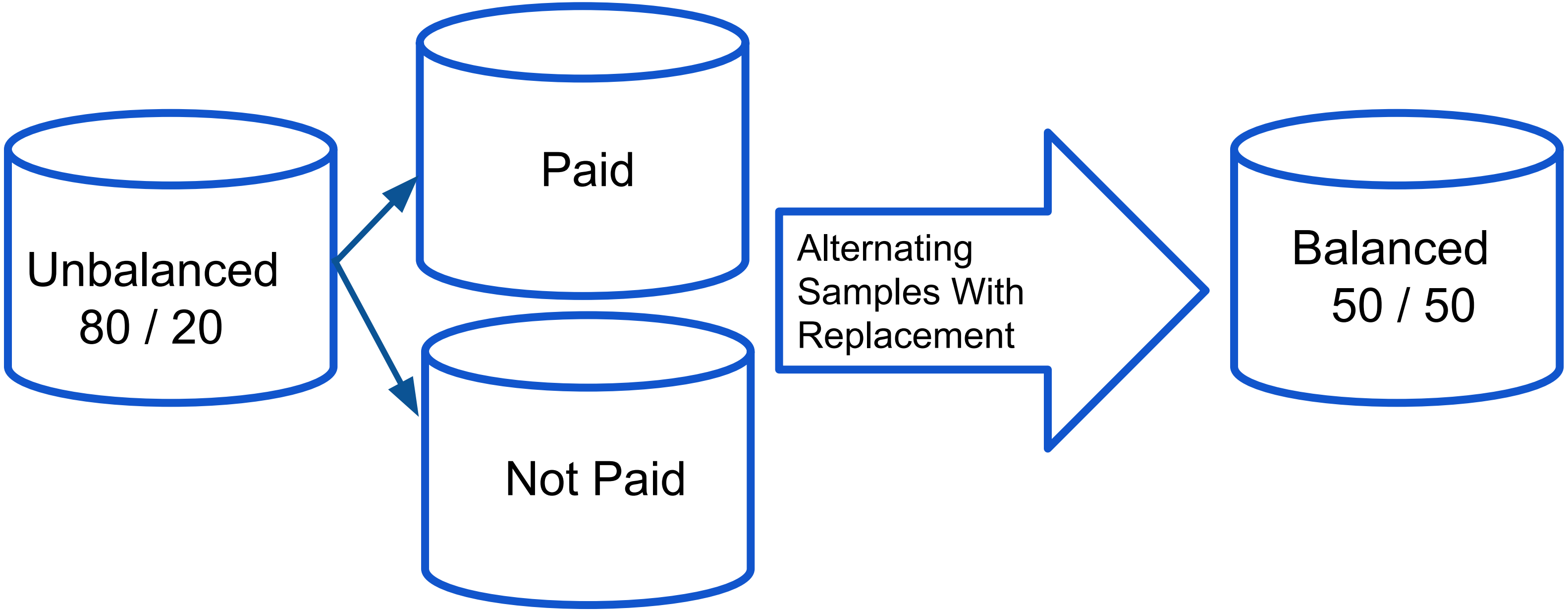
- areaUnderROC : 0.71
- Confusion matrix
  - Precision
  - Recall
  - Accuracy



Initial Test Results

	Random Forest
Precision	0.46
Recall	0.05
Accuracy	0.82

Balancing TRAIN Data



Test Results

	Random Forest (80/20 data)	Logistic Regression Model (50/50 data)	Random Forest Model (50/50 data)	Improvement
Precision	**0.46**	**0.29**	**0.28**	-37.23%
Recall	**0.05**	**0.66**	**0.65**	1215.09%
Accuracy	**0.82**	**0.64**	**0.64**	-21.48%

Test Results

```
metrics = MulticlassMetrics(sc.parallelize(predictionAndLabels))
print metrics.confusionMatrix().toArray()
print metrics.precision(1)
print metrics.recall(1)
print metrics.accuracy
```

```
[[ 25876.  14500.]
 [  3066.   5887.]]
0.288762446657
0.657544956998
0.64390115348
```

	Predicted Paid	Predicted Not Paid	Metrics
Actual Paid	**26,000 (53%)**	**14,500 (30%)**	Precision = 0.28
Actual Not Paid	**3,000 (5%)**	**6,000 (12%)**	Recall = 0.66

Lessons Learned

- Unbalanced training set can be problematic
- Recall is crucial in default detection
- Feature importance is hard to handle in ML
- Overhead issue with too many partitions

Thank you!