FannieMaeCorrectInputArray

⋆ Collapse

By marty (http://cdsw2.lurie.biz/marty) — Python 2 Session (Base Image v6) — 5 hours ago for 108 minutes

Timeout

Fannie Mae failed loan prediction

Model to predict if a loan will have foreclosure costs

keras requires python 2 / get tensorflow import error see forked project debugging pairplot cast all variables to fl choked on the decimal mixed with float limited the number of points in the guery to 5000 - cuts way down on the

```
from __future__ import print_function
  !echo $PYTHON_PATH
  import os, sys
import path
 from pyspark.sql import *
create spark sql session
 myspark = SparkSession\
      .builder\
      .appName("LoanPredictionSparkML_LogisticRegression") \
      .getOrCreate()
  sc = myspark.sparkContext
  import time
 print ( time.time())
  1569613399.82
  sc.setLogLevel("ERROR")
 print ( myspark )
  <pyspark.sql.session.SparkSession object at 0x7f668d851890>
make spark print text instead of octal
 myspark.sql("SET spark.sql.parquet.binaryAsString=true")
  DataFrame[key: string, value: string]
read in the data file from HDFS lots of sql cleanup, particularly removing NULL vals
/user/hive/warehouse/fanniemae.db/fannie_harp_sql_normed_p
use train dataset traindata_p
 loansdf = myspark.read.parquet ( "/user/hive/warehouse/fanniemae.db/traindata_p")
also read from s3 mydf = myspark.read.parquet ("s3a://impalas3a/sample_07_s3a_parquet") print number of ro
type of object
  1 - - - - d - - - - - ( )
```

```
toansur.cache()
```

```
DataFrame[label: tinyint, loan_identifier: string, channel: decimal(1,1), seller_name:
 intrate: decimal(20,14), loanamt: decimal(21,11), loan2val: decimal(18,14), numborrower
 le, creditscore: double, property_state: string, origination_date: string, fcl_costs: (
 (38, 12)
 print ( loansdf.count() )
 513866
 print ( loansdf )
 DataFrame[label: tinyint, loan_identifier: string, channel: decimal(1,1), seller_name:
 intrate: decimal(20,14), loanamt: decimal(21,11), loan2val: decimal(18,14), numborrower
 le, creditscore: double, property_state: string, origination_date: string, fcl_costs: (
 (38, 12)
 loansdf.show(5)
 |label|loan_identifier|channel|
                              seller_name|
                                              intrate|
          numborrowers|
                         creditscore|property_state|origination_date|
 n2val|
 PNC BANK, N.A. | 0.50000000000000 | 0.06633380884 | 1.08
        100004116882|
                     0.1|
     1|
 80412 | 0.166666666666666666 | 0.6247030878859857 |
                                           ILI
                                                    06/2014|0.0318460{
        100006935001|
                     0.1|DITECH FINANCIAL LLC|0.54838709677419|0.11768901569|0.94
 24742 | 0.3333333333333333 | 0.9513064133016627 |
                                                    05/2013|
                                           ILI
                     0.1|WELLS FARGO BANK,...|0.69354838709677|0.29172610556|0.96
        100007666444|
     0|
 84536 | 0.16666666666666666 | 0.828978622327791 |
                                           NY |
                                                    02/2010|
     01
        100015122571
                     0.1|JPMORGAN CHASE BA...|0.43548387096774|0.04136947218|0.87
 79381 | 0.16666666666666666 | 0.9382422802850356 |
                                                    03/2013|
                                           0H|
                     0.1|JPMORGAN CHASE BA...|0.54838709677419|0.06918687589|1.34
         100016186842|
 56701 | 0.3333333333333333 | 0.9109263657957245 |
 only showing top 5 rows
create a table name to use for queries
 loansdf.createOrReplaceTempView("loandata")
run a query data is already normalized foreclosure costs range from a value of 0 to 1
 lndf=myspark.sql('select * from loandata where fcl_costs < .9 limit 500000')</pre>
 lndf.show(5)
 |label|loan_identifier|channel|
                              seller_name|
                                              intrate|
                                                        loanamt|
          numborrowers|
                       creditscore|property_state|origination_date|
 ____+__
        100004116882|
                     0.1|
                            PNC BANK, N.A. | 0.50000000000000 | 0.06633380884 | 1.08
 80412 | 0.166666666666666666 | 0.6247030878859857 |
                                                    06/2014|0.0318460{
                                           ILI
         100006935001|
                     0.1|DITECH FINANCIAL LLC|0.54838709677419|0.11768901569|0.94
```

```
24742 | 0.3333333333333333 | 0.9513064133016627 |
                                                     05/2013|
                    0.1|WELLS FARGO BANK,...|0.69354838709677|0.29172610556|0.96
       100007666444|
   0|
84536 | 0.16666666666666666 | 0.828978622327791 |
                                            NY I
                                                     02/2010|
                    0.1|JPMORGAN CHASE BA...|0.43548387096774|0.04136947218|0.87
       100015122571|
79381 | 0.16666666666666666 | 0.9382422802850356 |
                                            0HI
                                                     03/20131
   0|
       100016186842|
                    0.1|JPMORGAN CHASE BA...|0.54838709677419|0.06918687589|1.34
56701 | 0.3333333333333333 | 0.9109263657957245 |
                                            ILI
                                                     01/2013|
only showing top 5 rows
```

lndf.count()

500000

pairplot to see what we have... not all cols are numeric, so we drop those for pair plot we will use string indexer I clean those up

```
import seaborn as sns
import pandas
```

debuging: convert all datatypes to float switch to python 3 note: case statement in impala will create a decimal f when a=b then 0.1 :-(

reduce total columns in the pair plot so it doesn't take too long to run

```
pplotdf1 =myspark.sql('select seller_name, float(channel),float(intrate),float(loanam
pplotdf1.show(3)
seller_name|channel| intrate| loanamt| loan2val|numborrowers|creditscore|
0.5|0.06633381|1.0824742| 0.16666667| 0.6247031|6
PNC BANK, N.A. | 0.1|
081
0.9513064
0.01
| WELLS FARGO BANK....| 0.1|0.6935484| 0.2917261|0.9072165| 0.16666667| 0.8289786|
0.01
only showing top 3 rows
```

seaborn wants a pandas dataframe, not a spark dataframe so convert

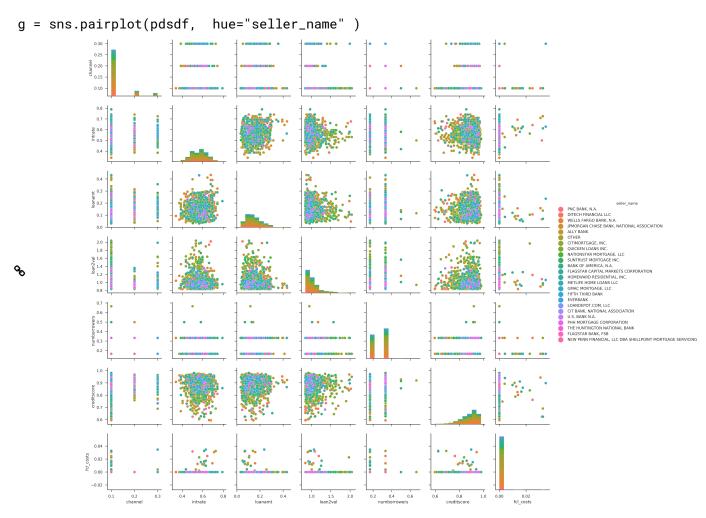
```
pdsdf = pplotdf1.toPandas()
pdsdf.head()
```

	seller_name	channel	intrate	loanamt	loan2val	numborrowers	creditscore
0	PNC BANK, N.A.	0.1	0.500000	0.066334	1.082474	0.166667	0.624703
1	DITECH FINANCIAL LLC	0.1	0.548387	0.117689	0.948454	0.333333	0.951306

2	WELLS FARGO BANK, N.A.	0.1	0.693548	0.291726	0.907216	0.166667	0.828979	
3	JPMORGAN CHASE BANK, NATIONAL ASSOCIATION	0.1	0.435484	0.041369	0.876289	0.166667	0.938242	
4	JPMORGAN CHASE BANK, NATIONAL ASSOCIATION	0.1	0.548387	0.069187	1.340206	0.333333	0.910926	

sns.set(style="ticks" , color_codes=True)

this takes a long time to run: you can see it if you uncomment it



Predict if a loan will have foreclosure costs

expand to all columns for machine learning

make the foreclosure costs binary a loan has "failed" if foreclosure > 0 in sql create column called "label" with 1 a

lndf = myspark.sql('select * from loandata ') #limit 500000')

Indf = myspark.sql('select * from loandata limit 500000')

Impala did much of the normalization

show an example here for those who want to use pyspark

need to convert from text field to numeric this is a common requirement when using sparkML

from pyspark.ml.feature import StringIndexer

this will convert each unique string into a numeric

```
indexer = StringIndexer(inputCol="property_state", outputCol="loc_state")
indexed = indexer.fit(lndf).transform(lndf)
indexed.show(5)
|label|loan_identifier|channel|
                           seller_name|
                                                   loanamt|
                                         intrate|
n2val|
         numborrowers|
                   creditscore|property_state|origination_date|
                                                        fcl_(
c_state|
1|
       100004116882|
                  0.1|
                         PNC BANK, N.A. | 0.50000000000000 | 0.06633380884 | 1.08
80412 | 0.166666666666666666 | 0.6247030878859857 |
                                       ILI
                                               06/2014|0.0318460{
3.0|
                  0.1|DITECH FINANCIAL LLC|0.54838709677419|0.11768901569|0.94
   0|
       100006935001|
24742 | 0.333333333333333 | 0.9513064133016627 |
                                       ILI
                                               05/2013|
3.0|
                  0.1|WELLS FARGO BANK,...|0.69354838709677|0.29172610556|0.96
       1000076664441
   01
84536 | 0.16666666666666666 | 0.828978622327791 |
                                       NY I
                                               02/2010|
12.0|
                  0.1|JPMORGAN CHASE BA...|0.43548387096774|0.04136947218|0.87
       100015122571|
79381 | 0.16666666666666666 | 0.9382422802850356 |
                                       OHI
                                               03/2013|
7.0|
                  0.1|JPMORGAN CHASE BA...|0.54838709677419|0.06918687589|1.34
       100016186842|
56701 | 0.3333333333333333 | 0.9109263657957245 |
                                       ILI
----+
only showing top 5 rows
```

First try a logistic regression

now we need to create a "label" and "features" input for using the sparkML library

This runs in the Cloudera Spark Cluster

note the column headers - label and features are keywords

```
output = assembler.transform(indexed)
 output.show(5)
 ----+
 |label|loan_identifier|channel|
                                  seller_name|
                                                   intrate|
 n2val|
            numborrowers|
                            creditscore|property_state|origination_date|
                                                                    fcl_(
                  features|
 c_state|
 ----+
                               PNC BANK, N.A. | 0.50000000000000 | 0.06633380884 | 1.08
     1|
         100004116882|
                       0.1
 80412 | 0.166666666666666666 | 0.6247030878859857 |
                                                ILI
                                                         06/2014 | 0.0318460 {
 3.0|[0.5,0.0663338088...|
     0|
         100006935001|
                       0.1|DITECH FINANCIAL LLC|0.54838709677419|0.11768901569|0.94
 24742 | 0.3333333333333333 | 0.9513064133016627 |
                                                ILI
                                                         05/2013|
 3.0 | [0.54838709677419...|
         100007666444|
                       0.1|WELLS FARGO BANK,...|0.69354838709677|0.29172610556|0.96
     0|
 84536 | 0.16666666666666666 | 0.828978622327791 |
                                                NY I
                                                         02/2010|
 12.0|[0.69354838709677...|
     01
         100015122571
                       0.1|JPMORGAN CHASE BA...|0.43548387096774|0.04136947218|0.87
 79381 | 0.16666666666666666 | 0.9382422802850356 |
                                                OHI
                                                         03/2013|
 7.0|[0.43548387096774...|
                       0.1|JPMORGAN CHASE BA...|0.54838709677419|0.06918687589|1.34
     0|
         100016186842|
 56701 | 0.3333333333333333 | 0.9109263657957245 |
                                                ILI
                                                         01/2013|
 3.0|[0.54838709677419...|
 -----+
 only showing top 5 rows
 output.count()
 513866
 from pyspark.ml.classification import LogisticRegression
Create a LogisticRegression instance. This instance is an Estimator.
 lr = LogisticRegression(maxIter=10, regParam=0.3)
Print out the parameters, documentation, and any default values.
 print("LogisticRegression parameters:\n" + lr.explainParams() + "\n")
 LogisticRegression parameters:
 aggregationDepth: suggested depth for treeAggregate (>= 2). (default: 2)
 elasticNetParam: the ElasticNet mixing parameter, in range [0, 1]. For alpha = 0, the parameter
 is an L2 penalty. For alpha = 1, it is an L1 penalty. (default: 0.0)
 family: The name of family which is a description of the label distribution to be used
 model. Supported options: auto, binomial, multinomial (default: auto)
 featuresCol: features column name. (default: features)
 fitIntercept: whether to fit an intercept term. (default: True)
 labelCol: label column name. (default: label)
 lowerBoundsOnCoefficients: The lower bounds on coefficients if fitting under bound cons
```

optimization. The bound matrix must be compatible with the shape (1, number of features inomial regression, or (number of classes, number of features) for multinomial regressi defined) lowerBoundsOnIntercepts: The lower bounds on intercepts if fitting under bound constrai imization. The bounds vector size must beequal with 1 for binomial regression, or the r flasses for multinomial regression. (undefined) maxIter: max number of iterations (>= 0). (default: 100, current: 10) predictionCol: prediction column name. (default: prediction) probabilityCol: Column name for predicted class conditional probabilities. Note: Not al s output well-calibrated probability estimates! These probabilities should be treated ? dences, not precise probabilities. (default: probability) rawPredictionCol: raw prediction (a.k.a. confidence) column name. (default: rawPredicti regParam: regularization parameter (>= 0). (default: 0.0, current: 0.3) standardization: whether to standardize the training features before fitting the model lt: True) threshold: Threshold in binary classification prediction, in range [0, 1]. If threshold resholds are both set, they must match.e.g. if threshold is p, then thresholds must be o [1-p, p]. (default: 0.5) thresholds: Thresholds in multi-class classification to adjust the probability of predi ach class. Array must have length equal to the number of classes, with values > 0, exce hat at most one value may be 0. The class with largest value p/t is predicted, where p original probability of that class and t is the class's threshold. (undefined) tol: the convergence tolerance for iterative algorithms (>= 0). (default: 1e-06) upperBoundsOnCoefficients: The upper bounds on coefficients if fitting under bound cons optimization. The bound matrix must be compatible with the shape (1, number of features inomial regression, or (number of classes, number of features) for multinomial regressi defined) upperBoundsOnIntercepts: The upper bounds on intercepts if fitting under bound constrai imization. The bound vector size must be equal with 1 for binomial regression, or the r f classes for multinomial regression. (undefined)

weightCol: weight column name. If this is not set or empty, we treat all instance weight

1.0. (undefined)

Learn a LogisticRegression model. This uses the parameters stored in Ir.

```
model1 = lr.fit(output)
```

Major shortcut - no train and test data!!!

Since model1 is a Model (i.e., a transformer produced by an Estimator), we can view the parameters it used durir This prints the parameter (name: value) pairs, where names are unique IDs for this LogisticRegression instance.

```
print("Model 1 was fit using parameters: ")
Model 1 was fit using parameters:
print(model1.extractParamMap())
```

{Param(parent=u'LogisticRegression_4515a8d50a7ae3d58d1d', name='featuresCol', doc='feat lumn name'): 'features', Param(parent=u'LogisticRegression_4515a8d50a7ae3d58d1d', name= cNetParam', doc='the ElasticNet mixing parameter, in range [0, 1]. For alpha = 0, the parameter, in range [0, 1]. is an L2 penalty. For alpha = 1, it is an L1 penalty'): 0.0, Param(parent=u'LogisticReq _4515a8d50a7ae3d58d1d', name='rawPredictionCol', doc='raw prediction (a.k.a. confidence n name'): 'rawPrediction', Param(parent=u'LogisticRegression_4515a8d50a7ae3d58d1d', nam l', doc='the convergence tolerance for iterative algorithms (>= 0)'): 1e-06, Param(pare

gisticRegression_4515a8d50a7ae3d58d1d', name='family', doc='The name of family which is ription of the label distribution to be used in the model. Supported options: auto, bir multinomial.'): 'auto', Param(parent=u'LogisticRegression_4515a8d50a7ae3d58d1d', name= m', doc='regularization parameter (>= 0)'): 0.3, Param(parent=u'LogisticRegression_451 ae3d58d1d', name='standardization', doc='whether to standardize the training features k itting the model'): True, Param(parent=u'LogisticRegression_4515a8d50a7ae3d58d1d', name bilityCol', doc='Column name for predicted class conditional probabilities. Note: Not a ls output well-calibrated probability estimates! These probabilities should be treated idences, not precise probabilities'): 'probability', Param(parent=u'LogisticRegression_ 50a7ae3d58d1d', name='aggregationDepth', doc='suggested depth for treeAggregate (>= 2) aram(parent=u'LogisticRegression_4515a8d50a7ae3d58d1d', name='predictionCol', doc='predictionCol', doc='prediction column name'): 'prediction', Param(parent=u'LogisticRegression_4515a8d50a7ae3d58d1d', r tIntercept', doc='whether to fit an intercept term'): True, Param(parent=u'LogisticRegi 4515a8d50a7ae3d58d1d', name='labelCol', doc='label column name'): 'label', Param(parent sticRegression_4515a8d50a7ae3d58d1d', name='maxIter', doc='maximum number of iterations 0)'): 10, Param(parent=u'LogisticRegression_4515a8d50a7ae3d58d1d', name='threshold', dc shold in binary classification prediction, in range [0, 1]'): 0.5}

trainingSummary = model1.summary

Obtain the objective per iteration

```
objectiveHistory = trainingSummary.objectiveHistory
print("objectiveHistory:")
```

objectiveHistory:

for objective in objectiveHistory:
 print(objective)

- 0.103031331693
- 0.102837131521
- 0.102673807922
- 0.102534456359
- 0.102523328224
- 0.10252332116
- 0.102523320957
- 0.102523319599
 0.102523318774
- 0.102523316697
- 0.102523309257

Obtain the receiver-operating characteristic as a dataframe and areaUnderROC. TPR true positive rate FPR false rate

trainingSummary.roc.show()

```
Cloudera Data Science Workbench · Enterprise Data Science Platform
   U.UUU004/0/UULIUZY| U.ZZ/00/U09U0UZU394|
  0.07624014761673732 | 0.25269603363187715 |
  0.08592749600337228 | 0.27691464083348566 |
   0.0956466583420159|
                        0.2996709925059404|
  0.10534991370465517 | 0.32324986291354413 |
  0.11509293650730527| 0.3450923048802778|
  0.12486777326196404| 0.3654724913178578|
  0.13465851699262713|
                          0.3852129409614331
  0.14448107467529886 | 0.40358252604642664 |
  0.15429766724196897 | 0.42186072016084813 |
   0.1640903993446326|
                          0.4413269968927071
      0.1738970500513| 0.46015353683056115|
   0.1836977356419658
                         0.47916285870955951
only showing top 20 rows
print("areaUnderROC: " + str(trainingSummary.areaUnderROC))
areaUnderROC: 0.737392082954
prediction = model1.transform(output)
prediction.show(10)
|label|loan_identifier|channel|
                                          seller_name|
                                                                intrate
n2val|
              numborrowers|
                                      rawPrediction|
c_state|
                     features|
```

```
-----+
                               creditscore|property_state|origination_date|
                                                                             fcl_(
                                                       probability|prediction|
-----
                            ----+
         100004116882|
                         0.1|
                                  PNC BANK, N.A. | 0.50000000000000 | 0.06633380884 | 1.08
80412 | 0.166666666666666666 | 0.6247030878859857 |
                                                     ILI
                                                                06/2014 | 0.0318460 {
3.0 \mid [0.5, 0.0663338088... \mid [3.73538045677095... \mid [0.97669213099883... \mid
         100006935001|
                         0.1|DITECH FINANCIAL LLC|0.54838709677419|0.11768901569|0.94
24742 | 0.333333333333333 | 0.9513064133016627 |
                                                     ILI
                                                                05/2013|
3.0|[0.54838709677419...|[3.88517236715389...|[0.97986928391875...]]
         100007666444|
                         0.1|WELLS FARGO BANK,...|0.69354838709677|0.29172610556|0.96
84536 | 0.16666666666666666 | 0.828978622327791 |
                                                                 02/20101
12.0|[0.69354838709677...|[3.74067522359799...|[0.97681236057540...|
                                                                      0.01
                         0.1|JPMORGAN CHASE BA...|0.43548387096774|0.04136947218|0.87
         100015122571|
79381 | 0.16666666666666666 | 0.9382422802850356 |
                                                     OHI
                                                                 03/2013|
7.0 \mid [0.43548387096774... \mid [3.91715139298351... \mid [0.98049049928748... \mid
                         0.1|JPMORGAN CHASE BA...|0.54838709677419|0.06918687589|1.34
         100016186842|
56701 | 0.333333333333333 | 0.9109263657957245 |
                                                     ILI
                                                                 01/2013|
3.0|[0.54838709677419...|[3.82782618604890...|[0.97870642176617...|
         100018762402|
                         0.1
                                       ALLY BANK | 0.54838709677419 | 0.12125534950 | 1.06
00000| 0.333333333333333| 0.6805225653206651 |
                                                     MNI
                                                                12/2012|
9.0|[0.54838709677419...|[3.77040059184264...|[0.97747618185931...|
                                                                     0.01
                                           OTHER | 0.53225806451612 | 0.09843081312 | 1.02
    01
         1000222482391
                         0.1
70103 | 0.166666666666666666 | 0.9394299287410927 |
                                                     MO I
                                                                05/2012|
21.0|[0.53225806451612...|[3.85371159813761...|[0.97923924569525...|
                                                                      0.01
         100026182562|
                         0.21
                                           OTHER | 0.62903225806451 | 0.16048502139 | 0.86
44329 | 0.3333333333333333 | 0.9453681710213777 |
                                                     MO I
                                                                12/2009|
```

```
21.0|[0.62903225806451...|[3.84962970833864...|[0.97915609937942...|
                                                                   0.0
                         0.1| CITIMORTGAGE, INC. | 0.51612903225806 | 0.09700427960 | 0.96
          100032945091
  94845 | 0.16666666666666666 | 0.8087885985748219 |
                                                    CAI
                                                              06/2013|
 0.0|[0.51612903225806...|[3.81387121506068...][0.97841364683026...]
                                                                  0.01
                         0.1|JPMORGAN CHASE BA...|0.64516129032258|0.17118402282|1.11
          100033142675|
  85567 | 0.3333333333333333 | 0.9489311163895487 |
                                                    NV I
  18.0|[0.64516129032258...|[3.81811618533423...|[0.97850312038437...|
                                                                   0.01
  only showing top 10 rows
 result = prediction.select("label", "probability", "prediction") \
     .collect()
print(result)
 true0=0
 false0=0
 true1=0
 false1=0
 i=0
 for row in result:
    if ( row.label == 0 and row.prediction ==0 ):
      true0=true0+1
    if ( row.label == 0 and row.prediction ==1 ):
      false1=false1+1
    if ( row.label == 1 and row.prediction ==1 ):
      true1=true1+1
    if ( row.label == 1 and row.prediction ==0 ):
      false0=false0+1
print("label=%s, prob=%s, prediction=%s" \ % (row.label, row.probability, row.prediction)) comment: don't break th
full error count if ( i > 10): break
 print ("true0=%i false0=%i true1=%i false1=%i"
                                                            false0 , true1 , fal
                                                % (true0 ,
 true0=502924 false0=10942 true1=0 false1=0
 trainingSummary.roc.show()
  +----+
                 FPRI
                                    TPR I
  +----+
                 0.01
                                    0.01
  [0.009273767010522465]0.043136538110034726]
  0.01876227819710334 | 0.07667702430999818 |
  [0.028280614963692326] 0.10866386401023578]
  |0.037838719170292134| 0.13891427526960337|
  0.04740278849289356 | 0.16898190458782672 |
    0.0569628810714939| 0.1991409248766222|
   0.0665547876021029| 0.22783768963626394|
  0.07624014761673732 | 0.25269603363187715 |
   0.08592749600337228 | 0.27691464083348566 |
    0.0956466583420159| 0.2996709925059404|
```

can we do better with a deep learning keras network?

https://medium.com/datadriveninvestor/building-neural-network-using-keras-for-classification-3a3656c726c1 (https://medium.com/datadriveninvestor/building-neural-network-using-keras-for-classification-3a3656c726c1)

This runs in the kubernetes-docker CDSW cluster

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

need dataframe for keras with only numerics

```
output.show(1)
-+----+
|label|loan_identifier|channel|
               seller_name|
                         intrate|
                               loanamt|
                                      10
numborrowers|
         creditscore|property_state|origination_date|
                               fcl_costs|loc_stat
features|
0.1|PNC BANK, N.A.|0.50000000000000000000001.06633380884|1.08247422
    100004116882|
                            06/2014|0.031846080481|
IL
0|[0.5,0.0663338088...|
-+----+
only showing top 1 row
```

kerasinputdf=output.drop('property_state','features','origination_date', 'loan_identifi

kerasinputdf.show(1)

kerasinputdf.count()

513866

kerasinputpsdf=kerasinputdf.toPandas()

kerasinputpsdf.head()

	label	channel	intrate	loanamt	loan2val	numborrowers	creditscore
0	1	0.1	0.500000000000000	0.06633380884	1.08247422680412	0.166667	0.624703
1	0	0.1	0.54838709677419	0.11768901569	0.94845360824742	0.333333	0.951306
2	0	0.1	0.69354838709677	0.29172610556	0.90721649484536	0.166667	0.828979
3	0	0.1	0.43548387096774	0.04136947218	0.87628865979381	0.166667	0.938242
4	0	0.1	0.54838709677419	0.06918687589	1.34020618556701	0.333333	0.910926

kerasinputpsdf.count()

label	513866
channel	513866
intrate	513866
loanamt	513866
loan2val	513866
numborrowers	513866
creditscore	513866
loc_state	513866

dtype: int64

kerasinputpsdf.describe(include='all')

	label	channel	intrate	loanamt	loan2val	numborro
count	513866.000000	513866	513866	513866	513866	513866.000
unique	NaN	3	1801	727	120	NaN
top	NaN	0.1	0.54838709677419	0.12125534950	0.97938144329896	NaN
freq	NaN	436097	42322	2563	20591	NaN
mean	0.021293	NaN	NaN	NaN	NaN	0.260434
std	0.144361	NaN	NaN	NaN	NaN	0.084680
min	0.000000	NaN	NaN	NaN	NaN	0.166667
25%	0.000000	NaN	NaN	NaN	NaN	0.166667

50%	0.000000	NaN	NaN	NaN	NaN	0.333333
75%	0.000000	NaN	NaN	NaN	NaN	0.333333
max	1.000000	NaN	NaN	NaN	NaN	1.333333

sns.heatmap(kerasinputpsdf.corr(), annot=True)

<matplotlib.axes._subplots.AxesSubplot at 0x7f6622cda310>



we should not have "peeked" at the full dataset :-)

traindataset at 80% of sample

train and test split

trainpdf=kerasinputpsdf.sample(frac=0.8, random_state=200)
testpdf=kerasinputpsdf.drop(trainpdf.index)

trainpdf

	label	channel	intrate	loanamt	loan2val	numborrowers	cred
65599	0	0.1	0.48387096774193	0.17546362339	0.90721649484536	0.333333	0.91
467918	0	0.1	0.59677419354838	0.09914407988	0.86597938144329	0.166667	0.77
89298	0	0.1	0.50000000000000	0.21255349500	1.000000000000000	0.166667	0.80
158714	0	0.3	0.61290322580645	0.23537803138	1.19587628865979	0.333333	0.81
313647	0	0.3	0.54838709677419	0.14835948644	0.86597938144329	0.333333	0.95
5718	0	0.2	0.61290322580645	0.21968616262	0.90721649484536	0.333333	0.95
286298	0	0.1	0.53225806451612	0.14122681883	1.65979381443298	0.166667	0.94
395366	0	0.1	0.50000000000000	0.25320970042	0.83505154639175	0.166667	0.90
494248	n	ი 1	0 58064516129032	n n5n64194nn8	1 83505154639175	ი 166667	0 96

	•	J U	0.0000 10 10 12 7002	0.00001121000	1.000001010007170	0.10000	0.50
359337	0	0.1	0.51612903225806	0.10199714693	1.14432989690721	0.166667	0.95
178143	0	0.1	0.43548387096774	0.13052781740	0.88659793814432	0.333333	0.76
503153	0	0.1	0.58064516129032	0.18188302425	1.31958762886597	0.333333	0.82
426179	0	0.1	0.61290322580645	0.09557774607	0.83505154639175	0.333333	0.86
154097	0	0.3	0.54838709677419	0.11840228245	1.14432989690721	0.166667	0.94
59076	0	0.1	0.66129032258064	0.23609129814	1.02061855670103	0.166667	0.92
28763	0	0.1	0.74193548387096	0.21398002853	1.21649484536082	0.333333	0.77
72786	0	0.1	0.66129032258064	0.13266761768	1.08247422680412	0.333333	0.72:
10182	0	0.1	0.56451612903225	0.13980028530	1.32989690721649	0.166667	0.95
486280	0	0.2	0.46774193548387	0.26105563480	0.97938144329896	0.166667	0.89
153755	0	0.2	0.56451612903225	0.22467902995	0.92783505154639	0.333333	0.95
476383	0	0.1	0.53225806451612	0.27888730385	1.19587628865979	0.166667	0.824
365230	0	0.1	0.500000000000000	0.06847360912	0.95876288659793	0.166667	0.90
348758	0	0.1	0.59677419354838	0.08844507845	1.52577319587628	0.333333	0.954
220536	0	0.1	0.61290322580645	0.28174037089	0.84536082474226	0.333333	0.92
97003	1	0.1	0.74193548387096	0.10199714693	1.05154639175257	0.333333	0.76
199997	0	0.1	0.59677419354838	0.12838801711	0.86597938144329	0.166667	0.92
260303	0	0.1	0.51483870967741	0.13409415121	1.10309278350515	0.166667	0.93
356829	0	0.1	0.51483870967741	0.19044222539	1.08247422680412	0.166667	0.75
288482	0	0.1	0.59677419354838	0.10413694721	1.06185567010309	0.333333	0.824
132024	0	0.1	0.53225806451612	0.08559201141	0.84536082474226	0.166667	0.90
		•••					
59471	0	0.1	0.46451612903225	0.11840228245	0.89690721649484	0.166667	0.94
510602	0	0.3	0.62903225806451	0.13266761768	1.51546391752577	0.333333	0.90
490487	0	0.1	0.66129032258064	0.04850213980	1.02061855670103	0.333333	0.83
273793	0	0.1	0.67741935483870	0.16262482168	1.35051546391752	0.166667	0.78
37768	0	0.1	0.56451612903225	0.17332382310	0.98969072164948	0.333333	0.85
307681	0	0.3	0.57935483870967	0.12910128388	0.97938144329896	0.166667	0.94
490969	0	0.1	0.54838709677419	0.21897289586	1.50515463917525	0.166667	0.834
438287	0	0.1	0.45161290322580	0.07631954350	0.90721649484536	0.166667	0.802
451014	0	0.1	0.61290322580645	0.24322396576	1.30927835051546	0.333333	0.84
77098	0	0.1	0.62903225806451	0.23038516405	1.08247422680412	0.333333	0.81
80431	0	0.1	0.48387096774193	0.12696148359	1.04123711340206	0.166667	0.954
112225	0	0.1	0.53225806451612	0.04707560627	0.91752577319587	0.166667	0.87
85348	0	0.1	0.45161290322580	0.07132667617	1.01030927835051	0.166667	0.874
192473	0	0.1	0.62903225806451	0.08059914407	1.02061855670103	0.166667	0.81

			I.	1	I.	1	
348204	0	0.1	0.51612903225806	0.17617689015	0.89690721649484	0.333333	0.959
162088	0	0.1	0.51612903225806	0.21683309557	0.90721649484536	0.333333	0.941
140724	0	0.1	0.54838709677419	0.25534950071	1.13402061855670	0.333333	0.76:
362894	0	0.1	0.37096774193548	0.15905848787	0.87628865979381	0.333333	0.80:
306627	0	0.1	0.58064516129032	0.25820256776	0.88659793814432	0.166667	0.94
183737	0	0.1	0.46774193548387	0.05777460770	0.86597938144329	0.333333	0.95
490581	0	0.1	0.48387096774193	0.21326676176	0.97938144329896	0.166667	0.910
409211	0	0.3	0.61290322580645	0.19900142653	0.97938144329896	0.333333	0.88
70446	0	0.1	0.58064516129032	0.11626248216	0.89690721649484	0.166667	0.84
69467	0	0.1	0.56451612903225	0.26676176890	0.95876288659793	0.333333	0.87
275809	0	0.1	0.53225806451612	0.26390870185	0.96907216494845	0.333333	0.94:
506799	0	0.1	0.69354838709677	0.08273894436	0.83505154639175	0.166667	0.904
425744	0	0.2	0.54838709677419	0.23537803138	0.92783505154639	0.333333	0.95
65258	0	0.1	0.74193548387096	0.12054208273	1.01030927835051	0.333333	0.76
343146	0	0.1	0.46451612903225	0.09129814550	0.87628865979381	0.333333	0.89
383516	0	0.1	0.51612903225806	0.17831669044	1.09278350515463	0.166667	0.82

411093 rows × 8 columns

testpdf

	label	channel	intrate	loanamt	loan2val	numborrowers	cred
0	1	0.1	0.50000000000000	0.06633380884	1.08247422680412	0.166667	0.62
2	0	0.1	0.69354838709677	0.29172610556	0.90721649484536	0.166667	0.82
8	0	0.1	0.51612903225806	0.09700427960	0.96907216494845	0.166667	0.80
9	0	0.1	0.64516129032258	0.17118402282	1.11340206185567	0.333333	0.94
13	0	0.1	0.50000000000000	0.15121255349	0.96907216494845	0.333333	0.94:
23	0	0.1	0.58064516129032	0.13980028530	1.73195876288659	0.333333	0.86
31	0	0.1	0.56451612903225	0.05349500713	0.90721649484536	0.333333	0.900
33	0	0.1	0.51612903225806	0.09272467902	0.93814432989690	0.166667	0.89
41	0	0.1	0.48387096774193	0.05706134094	0.83505154639175	0.166667	0.86
56	0	0.1	0.48387096774193	0.05206847360	1.25773195876288	0.166667	0.94
57	0	0.2	0.50000000000000	0.07203994293	1.08247422680412	0.333333	0.93
59	0	0.1	0.61290322580645	0.08630527817	0.95876288659793	0.166667	0.76
62	0	0.1	0.54838709677419	0.23965763195	0.97938144329896	0.166667	0.93
68	0	0.1	0.70967741935483	0.07631954350	0.94845360824742	0.333333	0.960
69	0	0.1	0.62903225806451	0.15121255349	0.90721649484536	0.333333	0.850
70	0	0.3	0.67741935483870	0.10841654778	1.02061855670103	0.333333	0.92
76	0	0.1	0.52903225806451	0.28102710413	0.98969072164948	0.166667	0.84

77	0	0.3	0.46774193548387	0.05135520684	1.06185567010309	0.333333	0.92
88	0	0.1	0.61290322580645	0.10912981455	1.03092783505154	0.333333	0.87
94	0	0.1	0.45161290322580	0.06419400855	0.90721649484536	0.333333	0.96
97	0	0.1	0.500000000000000	0.07631954350	0.88659793814432	0.166667	0.694
99	1	0.1	0.62903225806451	0.04921540656	1.25773195876288	0.166667	0.86
109	0	0.1	0.51612903225806	0.10342368045	0.94845360824742	0.333333	0.93
120	0	0.1	0.500000000000000	0.19044222539	1.03092783505154	0.333333	0.91:
145	0	0.1	0.500000000000000	0.17403708987	1.07216494845360	0.166667	0.81
151	0	0.1	0.56451612903225	0.15406562054	1.03092783505154	0.333333	0.90
157	0	0.1	0.43548387096774	0.13837375178	0.91752577319587	0.166667	0.81
163	0	0.1	0.64516129032258	0.20470756062	1.11340206185567	0.166667	0.90
165	0	0.1	0.56451612903225	0.16476462196	0.93814432989690	0.166667	0.60
167	0	0.3	0.500000000000000	0.22895863052	0.89690721649484	0.333333	0.84:
•••							
513696	0	0.3	0.58064516129032	0.12553495007	1.64948453608247	0.166667	0.92
513700	0	0.1	0.56451612903225	0.22111269614	1.18556701030927	0.166667	0.95
513712	0	0.1	0.66129032258064	0.03566333808	1.000000000000000	0.166667	0.849
513714	0	0.1	0.40322580645161	0.19044222539	1.10309278350515	0.333333	0.89
513716	0	0.1	0.56451612903225	0.11198288159	1.05154639175257	0.500000	0.94
513725	0	0.2	0.54838709677419	0.09985734664	1.69072164948453	0.166667	0.94
513726	0	0.1	0.58709677419354	0.15049928673	0.84536082474226	0.166667	0.83
513733	0	0.3	0.48387096774193	0.16975748930	0.85567010309278	0.166667	0.66
513734	0	0.1	0.53225806451612	0.17546362339	1.62886597938144	0.166667	0.814
513744	0	0.1	0.46774193548387	0.15263908701	0.84536082474226	0.166667	0.88
513759	0	0.1	0.61290322580645	0.06990014265	1.09278350515463	0.166667	0.85
513764	0	0.1	0.61290322580645	0.12339514978	1.22680412371134	0.333333	0.91
513769	0	0.1	0.54838709677419	0.13552068473	0.91752577319587	0.166667	0.74
513771	0	0.1	0.69354838709677	0.22681883024	1.000000000000000	0.333333	0.960
513782	0	0.1	0.70967741935483	0.10912981455	1.04123711340206	0.333333	0.93
513786	0	0.1	0.53225806451612	0.11198288159	0.86597938144329	0.333333	0.88
513789	0	0.1	0.59677419354838	0.11340941512	0.86597938144329	0.166667	0.839
513795	0	0.1	0.61290322580645	0.34593437945	0.88659793814432	0.166667	0.81
513797	0	0.1	0.38709677419354	0.07774607703	0.86597938144329	0.166667	0.969
513807	0	0.1	0.45161290322580	0.12767475035	0.83505154639175	0.333333	0.94
513809	0	0.1	0.56451612903225	0.28459343794	1.59793814432989	0.333333	0.92

513821	0	0.1	0.61290322580645	0.14764621968	0.93814432989690	0.333333	0.969
513822	0	0.1	0.56451612903225	0.11768901569	1.60824742268041	0.166667	0.92:
513838	0	0.1	0.51483870967741	0.22325249643	1.53608247422680	0.333333	0.88:
513850	0	0.1	0.56451612903225	0.12624821683	0.87628865979381	0.166667	0.93
513855	0	0.1	0.67741935483870	0.09129814550	1.28865979381443	0.333333	0.86
513858	0	0.1	0.64516129032258	0.05563480741	0.94845360824742	0.166667	0.59
513860	0	0.1	0.54838709677419	0.11982881597	1.21649484536082	0.166667	0.83
513864	0	0.1	0.45161290322580	0.06704707560	0.85567010309278	0.166667	0.79

102773 rows × 8 columns

creating input features and target variables

```
X= trainpdf.iloc[:,1:7]
y= trainpdf.iloc[:,0]
```

X.head()

	channel	intrate	loanamt	loan2val	numborrowers	creditscore
65599	0.1	0.48387096774193	0.17546362339	0.90721649484536	0.333333	0.916865
467918	0.1	0.59677419354838	0.09914407988	0.86597938144329	0.166667	0.779097
89298	0.1	0.500000000000000	0.21255349500	1.000000000000000	0.166667	0.809976
158714	0.3	0.61290322580645	0.23537803138	1.19587628865979	0.333333	0.813539
313647	0.3	0.54838709677419	0.14835948644	0.86597938144329	0.333333	0.951306

y.head()

65599 0 467918 0 89298 0 158714 0 313647 0

Name: label, dtype: int8

from sklearn.cross_validation import train_test_split

import sklearn from sklearn.model_selection import train_test_split from sklearn import train_test_split X_train, > y_train, y_test = train_test_split(X, y, test_size=0.3)

!pip install -upgrade -force-reinstall tensorflow !pip install -upgrade -force-reinstall keras

```
import tensorflow as tf
import keras as ks
```

Using TensorFlow backend.

```
from keras import Sequential
from keras.layers import Dense
from keras.callbacks import TensorBoard
```

tutorial from tensorflow.keras.callbacks import TensorBoard

```
classifier = Sequential()
```

```
First Hidden Layer
 classifier.add(Dense(16, activation='relu', kernel_initializer='random_normal', input_d
Second Hidden Layer
 classifier.add(Dense(20, activation='relu', kernel_initializer='random_normal'))
Output Layer
 classifier.add(Dense(1, activation='sigmoid', kernel_initializer='random_normal'))
Compiling the neural network
 classifier.compile(optimizer ='adam',loss='binary_crossentropy', metrics =['accuracy'])
  WARNING:tensorflow:From /home/cdsw/.local/lib/python2.7/site-packages/tensorflow/pythor
  _impl.py:180: where (from tensorflow.python.ops.array_ops) is deprecated and will be re
  n a future version.
  Instructions for updating:
  Use tf.where in 2.0, which has the same broadcast rule as np.where
tbcallback = tb(log_dir='/tmp/tblog', histogram_freq=0, write_graph=True, write_images=True)
upgrade dask to fix? fork first to save working project !pip install -upgrade -force-reinstall dask tensorboard =
TensorBoard(log_dir="/tmp/tblogs")
Fitting the data to the training dataset classifier.fit(X,y, batch_size=10, epochs=50, verbose=1, callbacks=[tbcallbacks=1]
small batch size of 10 is hurting performance moving to 32
 classifier.fit(X,y, batch_size=32, epochs=10, verbose=1)
  ValueError: Error when checking input: expected dense_1_input to have shape (7,) but go
  ValueErrorTraceback (most recent call last)
  in engine
  ----> 1 classifier.fit(X,y, batch_size=32, epochs=10, verbose=1)
  /home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training.pyc in fit(self, x,
     1152
                       sample_weight=sample_weight,
     1153
                       class_weight=class_weight,
  -> 1154
                       batch_size=batch_size)
     1155
     1156
                   # Prepare validation data.
  /home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training.pyc in _standardize
      577
                       feed_input_shapes,
      578
                       check_batch_axis=False, # Don't enforce the batch size.
                       exception_prefix='input')
  --> 579
      580
      581
                   if y is not None:
  /home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training_utils.pyc in standa
                                         ': expected ' + names[i] + ' to have shape ' +
      143
                                        str(shape) + ' but got array with shape ' +
      144
  --> 145
                                        str(data_shape))
```

return data

146147

ValueError: Error when checking input: expected dense_1_input to have shape (7,) but go

trainpdf.head

<bookspace </bookspace loan2val	thod Da	ataFram	ne.head of	label channel	intrate	loanam
65599	, 0	0.1	0.48387096774193	0.17546362339	0.90721649484536	
467918	0	0.1	0.59677419354838	0.09914407988	0.86597938144329	
89298	0	0.1	0.500000000000000	0.21255349500	1.000000000000000	
158714	0	0.3	0.61290322580645	0.23537803138	1.19587628865979	
313647	0	0.3	0.54838709677419	0.14835948644	0.86597938144329	
5718	0	0.2	0.61290322580645	0.21968616262	0.90721649484536	
286298	0	0.1	0.53225806451612	0.14122681883	1.65979381443298	
395366	0	0.1	0.500000000000000	0.25320970042	0.83505154639175	
494248	0	0.1	0.58064516129032	0.05064194008	1.83505154639175	
359337	0	0.1	0.51612903225806	0.10199714693	1.14432989690721	
178143	0	0.1	0.43548387096774	0.13052781740	0.88659793814432	
503153	0	0.1	0.58064516129032	0.18188302425	1.31958762886597	
426179	0	0.1	0.61290322580645	0.09557774607	0.83505154639175	
154097	0	0.3	0.54838709677419	0.11840228245	1.14432989690721	
59076		0.3	0.66129032258064	0.23609129814	1.02061855670103	
28763	0	0.1	0.74193548387096	0.21398002853		
	0		0.66129032258064	0.13266761768	1.21649484536082 1.08247422680412	
72786	0	0.1				
10182	0	0.1	0.56451612903225	0.13980028530	1.32989690721649	
486280	0	0.2	0.46774193548387	0.26105563480	0.97938144329896	
153755	0	0.2	0.56451612903225	0.22467902995	0.92783505154639	
476383	0	0.1	0.53225806451612	0.27888730385	1.19587628865979	
365230	0	0.1	0.500000000000000	0.06847360912	0.95876288659793	
348758	0	0.1	0.59677419354838	0.08844507845	1.52577319587628	
220536	0	0.1	0.61290322580645	0.28174037089	0.84536082474226	
97003	1	0.1	0.74193548387096	0.10199714693	1.05154639175257	
199997	0	0.1	0.59677419354838	0.12838801711	0.86597938144329	
260303	0	0.1	0.51483870967741	0.13409415121	1.10309278350515	
356829	0	0.1	0.51483870967741	0.19044222539	1.08247422680412	
288482	0	0.1	0.59677419354838	0.10413694721	1.06185567010309	
132024	0	0.1	0.53225806451612	0.08559201141	0.84536082474226	
 59471	0	0.1	0.46451612903225	0.11840228245	0.89690721649484	
510602	0	0.3	0.62903225806451		1.51546391752577	
490487	0	0.1	0.66129032258064		1.02061855670103	
273793	0	0.1	0.67741935483870	0.16262482168	1.35051546391752	
37768	0	0.1	0.56451612903225		0.98969072164948	
307681	0	0.3	0.57935483870967		0.97938144329896	
490969	0	0.1	0.54838709677419	0.21897289586	1.50515463917525	
438287	0	0.1	0.45161290322580	0.07631954350	0.90721649484536	
451014	0	0.1	0.61290322580645		1.30927835051546	
77098	0	0.1	0.62903225806451	0.23038516405	1.08247422680412	
80431	0	0.1	0.48387096774193	0.12696148359	1.04123711340206	
112225	0	0.1	0.53225806451612	0.04707560627	0.91752577319587	
35348			0.45161290322580	0.07132667617		
	0	0.1			1.01030927835051	
192473	0	0.1	0.62903225806451	0.08059914407	1.02061855670103	
348204	0	0.1	0.51612903225806	0.17617689015	0.89690721649484	
162088	0	0.1	0.51612903225806	0.21683309557	0.90721649484536	
140724	0	0.1	0.54838709677419	0.25534950071	1.13402061855670	

438287

0.166667

-013		Cloudera Data Science	Workberien Enterpris	se bata science i lationii
362894	0 0.1	0.37096774193548	0.15905848787	0.87628865979381
306627	0 0.1	0.58064516129032	0.25820256776	0.88659793814432
183737	0 0.1	0.46774193548387	0.05777460770	0.86597938144329
490581	0 0.1	0.48387096774193	0.21326676176	0.97938144329896
409211	0 0.3	0.61290322580645	0.19900142653	0.97938144329896
70446	0 0.1		0.11626248216	0.89690721649484
69467	0 0.1		0.26676176890	0.95876288659793
275809	0 0.1		0.26390870185	0.96907216494845
506799	0 0.1		0.08273894436	0.83505154639175
425744	0 0.2	0.54838709677419	0.23537803138	0.92783505154639
65258	0 0.1	0.74193548387096	0.12054208273	1.01030927835051
343146	0 0.1	0.46451612903225	0.09129814550	0.87628865979381
383516	0 0.1	0.51612903225806	0.17831669044	1.09278350515463
	numborrowers	creditscore loc_s	state	
65599	0.333333	0.916865	22.0	
467918	0.166667	0.779097	2.0	
89298	0.166667	0.809976	24.0	
158714	0.333333	0.813539	2.0	
313647	0.333333	0.951306	13.0	
5718	0.333333	0.956057	29.0	
286298	0.166667	0.945368	1.0	
395366	0.166667	0.901425	10.0	
494248	0.166667	0.960808	1.0	
359337	0.166667	0.956057	5.0	
178143	0.333333	0.763658	36.0	
503153	0.333333	0.823040	1.0	
426179	0.333333	0.863420	9.0	
154097	0.166667	0.944181	14.0	
59076	0.166667	0.921615	23.0	
28763	0.333333	0.777910	12.0	
72786	0.333333	0.722090	1.0	
10182	0.166667	0.951306	3.0	
486280	0.166667	0.895487	11.0	
153755	0.333333	0.951306	8.0	
476383	0.166667	0.824228	8.0	
365230	0.166667	0.903800	21.0	
348758	0.333333	0.954869	1.0	
220536	0.333333	0.925178	3.0	
97003	0.333333	0.767221	3.0	
199997	0.166667	0.923990	8.0	
260303	0.166667	0.931116	16.0	
356829	0.166667	0.758907	19.0	
288482	0.333333	0.824228	4.0	
132024	0.166667	0.909739	7.0	
59471	0.166667	0.941805	16.0	
510602	0.333333	0.941885	1.0	
490487	0.333333	0.833729	21.0	
273793	0.166667	0.785036	3.0	
37768	0.333333	0.858670	12.0	
307681	0.166667	0.948931	1.0	
490969	0.166667	0.834917	11.0	
400007	0.100007	0.00050	1.0	

1.0

0.802850

J 1 J			Cidadera Data Scienc	CVVOIRDC
457	0 14	0.333333	0.846/93	11.0
770	98	0.333333	0.811164	20.0
804	31	0.166667	0.954869	12.0
112	225	0.166667	0.875297	19.0
853	48	0.166667	0.874109	19.0
192	473	0.166667	0.818290	7.0
348	204	0.333333	0.959620	23.0
162	088	0.333333	0.940618	42.0
140	724	0.333333	0.762470	4.0
362	894	0.333333	0.802850	19.0
306	627	0.166667	0.946556	12.0
183	737	0.333333	0.953682	2.0
490	581	0.166667	0.910926	8.0
409	211	0.333333	0.888361	11.0
704	46	0.166667	0.845606	15.0
694	67	0.333333	0.875297	40.0
275	809	0.333333	0.942993	5.0
506	799	0.166667	0.904988	2.0
425	744	0.333333	0.959620	9.0
652	58	0.333333	0.768409	9.0
343	146	0.333333	0.891924	21.0
383	516	0.166667	0.823040	10.0

[411093 rows x 8 columns]>

creating input features and target variables

X= trainpdf.iloc[:,1:6]
y= trainpdf.iloc[:,0]

X.head()

	channel	intrate	loanamt	loan2val	numborrowers
65599	0.1	0.48387096774193	0.17546362339	0.90721649484536	0.333333
467918	0.1	0.59677419354838	0.09914407988	0.86597938144329	0.166667
89298	0.1	0.500000000000000	0.21255349500	1.000000000000000	0.166667
158714	0.3	0.61290322580645	0.23537803138	1.19587628865979	0.333333
313647	0.3	0.54838709677419	0.14835948644	0.86597938144329	0.333333

y.head()

65599 0 467918 0 89298 0 158714 0 313647 0

Name: label, dtype: int8

from sklearn.cross_validation import train_test_split

import sklearn from sklearn.model_selection import train_test_split from sklearn import train_test_split X_train, > y_train, y_test = train_test_split(X, y, test_size=0.3)

!pip install -upgrade -force-reinstall tensorflow !pip install -upgrade -force-reinstall keras

import tensorflow as tf

```
import keras as ks
 from keras import Sequential
 from keras.layers import Dense
 from keras.callbacks import TensorBoard
tutorial from tensorflow.keras.callbacks import TensorBoard
 classifier = Sequential()
First Hidden Layer
 classifier.add(Dense(16, activation='relu', kernel_initializer='random_normal', input_d
Second Hidden Layer
 classifier.add(Dense(20, activation='relu', kernel_initializer='random_normal'))
Output Layer
 classifier.add(Dense(1, activation='sigmoid', kernel_initializer='random_normal'))
Compiling the neural network
 classifier.compile(optimizer ='adam',loss='binary_crossentropy', metrics =['accuracy'])
tbcallback = tb(log_dir='/tmp/tblog', histogram_freq=0, write_graph=True, write_images=True)
upgrade dask to fix? fork first to save working project !pip install -upgrade -force-reinstall dask tensorboard =
TensorBoard(log_dir="/tmp/tblogs")
Fitting the data to the training dataset classifier.fit(X,y, batch_size=10, epochs=50, verbose=1, callbacks=[tbcallbacks]
small batch size of 10 is hurting performance moving to 32
 classifier.fit(X,y, batch_size=32, epochs=10, verbose=1)
  ValueError: Error when checking input: expected dense_4_input to have shape (7,) but go
  ValueErrorTraceback (most recent call last)
  in engine
  ----> 1 classifier.fit(X,y, batch_size=32, epochs=10, verbose=1)
  /home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training.pyc in fit(self, x,
     1152
                       sample_weight=sample_weight,
     1153
                       class_weight=class_weight,
  -> 1154
                       batch_size=batch_size)
     1155
                   # Prepare validation data.
     1156
  /home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training.pyc in _standardize
      577
                       feed_input_shapes.
      578
                       check_batch_axis=False, # Don't enforce the batch size.
                       exception_prefix='input')
  --> 579
      580
      581
                   if y is not None:
  /home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training_utils.pyc in standa
                                         ': expected ' + names[i] + ' to have shape ' +
      143
      144
                                         str(shape) + ' but got array with shape ' +
  --> 145
                                         str(data shape))
```

```
146    return data
147
```

ValueError: Error when checking input: expected dense_4_input to have shape (7,) but go

creating input features and target variables

```
X= trainpdf.iloc[:,1:7]
y= trainpdf.iloc[:,0]
```

X.head()

	channel	intrate	loanamt	loan2val	numborrowers	creditscore
65599	0.1	0.48387096774193	0.17546362339	0.90721649484536	0.333333	0.916865
467918	0.1	0.59677419354838	0.09914407988	0.86597938144329	0.166667	0.779097
89298	0.1	0.500000000000000	0.21255349500	1.000000000000000	0.166667	0.809976
158714	0.3	0.61290322580645	0.23537803138	1.19587628865979	0.333333	0.813539
313647	0.3	0.54838709677419	0.14835948644	0.86597938144329	0.333333	0.951306

```
y.head()
```

```
65599 0
467918 0
89298 0
158714 0
313647 0
Name: label, dtype: int8
```

from sklearn.cross_validation import train_test_split

import sklearn from sklearn.model_selection import train_test_split from sklearn import train_test_split X_train, y_test = train_test_split(X, y, test_size=0.3)

!pip install -upgrade -force-reinstall tensorflow !pip install -upgrade -force-reinstall keras

```
import tensorflow as tf
import keras as ks
from keras import Sequential
from keras.layers import Dense
from keras.callbacks import TensorBoard
```

tutorial from tensorflow.keras.callbacks import TensorBoard

```
classifier = Sequential()
```

First Hidden Layer

```
classifier.add(Dense(16, activation='relu', kernel_initializer='random_normal', input_d
Second Hidden Layer
```

```
classifier.add(Dense(20, activation='relu', kernel_initializer='random_normal'))
```

Output Layer

```
classifier.add(Dense(1, activation='sigmoid', kernel_initializer='random_normal'))
```

Compiling the neural network

```
classifier.compile(optimizer ='adam',loss='binary_crossentropy', metrics =['accuracy'])
tbcallback = tb(log_dir='/tmp/tblog', histogram_freq=0, write_graph=True, write_images=True)
```

upgrade dask to fix? fork first to save working project !pip install -upgrade -force-reinstall dask tensorboard = TensorBoard(log_dir="/tmp/tblogs")

Fitting the data to the training dataset classifier.fit(X,y, batch_size=10, epochs=50, verbose=1, callbacks=[tbcallbacks] small batch size of 10 is hurting performance moving to 32

```
classifier.fit(X,y, batch_size=32, epochs=10, verbose=1)
```

```
2019-09-27 19:51:08.214794: I tensorflow/core/platform/cpu_feature_quard.cc:142] Your (
orts instructions that this TensorFlow binary was not compiled to use: AVX2 FMA
2019-09-27 19:51:08.222354: I tensorflow/core/platform/profile_utils/cpu_utils.cc:94] (
uency: 2591990000 Hz
2019-09-27 19:51:08.223124: I tensorflow/compiler/xla/service/service.cc:168] XLA servi
aab550 executing computations on platform Host. Devices:
2019-09-27 19:51:08.223188: I tensorflow/compiler/xla/service/service.cc:175]
device (0): <undefined>, <undefined>
2019-09-27 19:51:08.365930: W tensorflow/compiler/jit/mark_for_compilation_pass.cc:1412
time warning): Not using XLA:CPU for cluster because envvar TF_XLA_FLAGS=--tf_xla_cpu_<
it was not set. If you want XLA:CPU, either set that envvar, or use experimental_jit_@
enable XLA:CPU. To confirm that XLA is active, pass --vmodule=xla_compilation_cache=1
roper command-line flag, not via TF_XLA_FLAGS) or set the envvar XLA_FLAGS=--xla_hlo_pr
WARNING:tensorflow:From /home/cdsw/.local/lib/python2.7/site-packages/keras/backend/ter
_backend.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.gl
riables instead.
```

Epoch 1/10

13 14 14 14 14 15 15 159 16 16 17 17 17 17 18 18 189 19 19 20 20 20 21 21 21 21 22 2 23 23 24 24 25 25 26 26 26 26 27 27 27 27 28 28 28 28 28 28 29 29 30 30 30 31 31 321 32 33 337 34 34 34 35 35 35 35 35 36 36 36 36 37 37 37 38 38 38 39 39 39 40 40 40 41 41 41 42 43 43 44 44 44 45 45 45 46 46 47 47 47 47 48 48 48 48 49 49 50 50 50 50 51 51 51 52 3 53 54 54 55 55 55 56 56 56 57 57 57 57 58 58 58 58 59 59 59 59 60 60 60 61 61 61 62 (63 63 63 64 64 64 65 65 65 65 66 66 66 66 67 67 67 68 68 68 68 68 68 69 69 69 70 70 1 71 72 72 73 73 74 74 75 75 75 76 76 76 77 77 77 78 78 78 78 78 79 79 79 79 80 80 80 8 80 81 81 81 81 81 82 82 82 82 83 83 83 83 84 84 84 85 85 85 85 86 86 86 86 87 87 8 88 88 88 89 89 89 90 90 90 91 91 92 92 92 93 93 93 94 94 94 95 95 95 96 96 96 96 98 98 98 99 99 99100100100100101101101101102102102102103103103103104104104104105105 117117118118118119119120120121121121122122123123124124124125125125126126127127127128128 214214314314414414414514514614614714714814814914915015115115115215215315315415415415515 156157157158158159159159160160160161161162162163163164164164165165166166167167168168169 70171171172172173173174175175176176177178178179179180181181182182182183183184184184 618618718718818818918919019019119119219219219319319419419419519519619619619719719819819 200200201202202203203204204205206206207207208208209209210210211211211211212212213213213 142152152162162172172172182182192192202202202212212212222222232232242242252252252262262 822822922923023123123223223323323423523523623623623723723823823923924024024024124124224 2432432442442442442452452452462462472472472482482492492492502502502512512522522522522525 542552552562562562572572582582582592592602602612612612622622632632632642642642652652662

13 14 14 15 15 15 16 16 17 17 18 18 19 19 20 20 20 21 21 22 22 23 23 23 24 24 25 25 2 27 27 27 28 28 28 29 29 30 30 30 31 31 32 32 33 33 33 34 34 35 35 36 36 37 37 38 38 39 0 41 42 42 43 43 44 44 44 45 45 46 46 46 47 47 48 48 48 49 49 49 50 50 50 51 51 51 52 \$ 53 53 54 54 55 55 55 56 56 56 57 57 57 57 58 58 58 58 59 59 59 59 60 60 60 61 61 61 62 3 63 64 64 64 65 65 65 66 66 67 67 68 68 69 69 70 70 71 71 72 72 73 73 73 74 74 75 7 76 77 77 78 78 78 79 79 79 80 80 80 81 81 81 82 82 82 83 83 83 84 84 84 84 85 85 85 86 7 87 88 88 89 89 89 90 90 91 91 92 92 93 93 94 94 94 95 95 96 96 96 97 97 98 98 98 99 9 101101102102102103103103104104104104105105105105106106106106107107108108108109109110116 112212212212212212212312312312412412412412512512612612612712712712712812812812912912912 131131131132132132133133133133134134134134134135135135135136136136137137137137138138138 39140140140141141142142142143143144144144145145146146147147148148148149149150150150151 115115215215215215315315315315315415415415515515515515615615615715715715815815815815915915 16016116116116116216216316316416416416516516616616716716816816916916917017017117117172 731731741741751751761761761771771771781781781791791791801801801811811811821821821831831 418518518518618618718718818818818918919019019119119219219319319319419419519519519619619 198198199199200200200201201202202203203203204204205205205206206206207207208208208208 092092102102102112112122122122132132142142142152152162162172172182182182182192192202202 234234235235236236236237237237238238239239240240240241241242242243243244244245245245246 472482482482482492492502502512512522522532542542552552562562572572572582582592592602 126126226226326326326426426426526526526626626726726726826826826926927027127127227227327 276276277277278278279280280281281282282283284284285286286287287288288289290290291291292 942942952952962962972972972982982993003003013023023033033043043053063063073073083083083 031031131131231231231331431431531531631731731831931932032132132232332432432532532632 32832932932933033133133233233233333333463353363363373373383393403403403413413423423433 61362363363364364365365366366367367368369369370370371372372373373374375375376377377378 038038138238338338438538638738838838938939039139139239339339439539539639639739739839939 401401402402402402403403404404405405405406406407407408408409409410410411093/411093 [=== =========] - 50s 123us/step - loss: 0.0959 - accuracy: 0.9787 Epoch 3/10

1 62 62 62 62 62 62 63 63 63 63 63 63 64 64 64 64 64 65 65 65 65 65 65 65 65 65 65 0 70 70 70 70 71 71 71 71 71 71 71 71 71 72 72 72 72 72 72 73 73 73 73 73 73 73 73 73 73 73 74 74 74 74 74 74 74 74 74 74 74 75 75 75 75 75 75 76 76 76 76 76 76 77 77 77 77 77 8 78 78 78 78 78 79 79 79 79 79 79 79 80 80 80 80 80 80 81 81 81 81 82 82 82 82 83 83 8 84 84 85 85 85 86 86 86 87 87 88 88 88 88 88 89 89 89 90 90 90 91 91 91 92 92 92 3 93 93 94 94 94 94 94 95 95 95 95 96 96 96 97 97 98 98 98 99 9910010010110110210216 61271271271281281281291291301301301311311311321321321331331341341341351351361361361361361 138139139140140140141141141141141141142142142142142142143143143143143143144144144144144 451451461461461471471481491491501501511521521531541541551551561561571571581581581591601 717717717817817817917918018018118218218218318318318418418518618618718818818919019019119 192193193194194195195196197198198199200201201202202202203203203204204205205206207207208 102102102102112112122122132142142152162162172172172182192192202202212212222232232242252 722722822922923023023123123223323323423523623623723823923924024024024124124124224224224 244245245246246247248248249249250251251252253253254255255256257258258259260260261262263 652652662662662672672682682692692692702702712712722722732732742742742752752762762762777 827827927928028128128228328328428428528528528628628728828828929029029129229229329429 296296296297297298298299300300301302302303304304305306306307308308309309310310311312312 143153153163173173183183193193203213223232324324325326326327328328329330331331332333 53353363373373383383393403403413423433433433443443453463463473483483493503503513513 235335335435435535535635635735735835935936036136236236336436436536636736736836937037037 373374374375376376377378378379379380381381382382383384384385385386387387388388389389389 913913923923933943943953953963973973983993994004014014024024034034044054054064064074084 0.9787

Epoch 4/10

14 14 15 15 16 17 17 18 18 19 19 20 21 21 22 22 23 24 24 25 26 27 27 28 29 29 30 31 3 33 34 34 35 36 36 37 38 39 39 40 41 41 42 42 43 43 44 45 45 46 46 47 47 48 49 50 51 51 3 54 54 55 56 56 57 58 58 59 59 60 60 61 62 62 63 64 65 65 66 67 67 68 69 69 70 71 72 7 74 75 76 76 77 78 79 80 80 81 82 83 83 84 85 86 86 87 88 89 90 90 91 92 92 93 94 95 95 7 97 98 98 99 99100100101101102102103103104104105106106107108109109110111111111211211311 33133134134135135136136137137138139139139140140141141142142143144144145145145146146147 161161162162162163163164164165165166166167167168168169169170170171171172173173174174174 818918918919019019019119119219219319319419419419519519619619719719819919920020120120226 20520520620720720820920921021021121121121221221321421421521521621621721821922022022122 242242252252262262272272282292292302302312312322322332332342352352352352362362372382382 02412412422422432442442452452462462472472482482492492502502502512512512522522532532542 25625625625725725825925926026026026126126226226326326426526526626626726826826927027027 73274274275276276277278278279280280281282282282832842852852862862872882882892902902912922 329429529529529629629729829829829929930030130130230263033033043053053063073073083093093 23133133143153153163163173183183193193203213213223233233243253253263273273283293293293 331332332333334334335335336336337337338339339340340341342342343344344345346346347348349 513523523533543553563563573583593593603613613623633643643653663663673683683693703713713 337437537537537637737737837937938038038138138238238338338438438538538638738738838838 391391392392393393394394394395395396396397397397398398399399400400401401402403403404404 05406406407407407408408408409409409410410410410411093/411093 [================== ====] - 38s 92us/step - loss: 0.0954 - accuracy: 0.9787

139 14 15 15 16 16 17 18 18 19 20 20 21 21 22 23 23 24 24 25 25 26 27 27 28 28 29 30 3

Truncating text at 800000 characters to improve display performance. Increase this limit with the environment variable 'MAX_TEXT_LENGTH'

classifier.summary()

```
Model: "sequential_3"
Layer (type)
               Output Shape
______
dense_7 (Dense)
               (None, 16)
                              112
______
dense_8 (Dense)
               (None, 20)
                              340
dense_9 (Dense)
               (None, 1)
______
Total params: 473
Trainable params: 473
Non-trainable params: 0
```

print(classifier.metrics()

save the classifier to deploy

what do the input features look like

X.head

<body> val \</body>	ethod D	ataFrame.head of	channel	intrate	loanamt
65599	0.1	0.48387096774193	0.17546362339	0.90721649484536	
467918	0.1	0.59677419354838	0.09914407988	0.86597938144329	
89298	0.1	0.500000000000000	0.21255349500	1.000000000000000	
158714	0.3	0.61290322580645	0.23537803138	1.19587628865979	
313647	0.3	0.54838709677419	0.14835948644	0.86597938144329	
5718	0.2	0.61290322580645	0.21968616262	0.90721649484536	

```
286298
                 0.53225806451612
                                                    1.65979381443298
           0.1
                                    0.14122681883
395366
           0.1
                 0.50000000000000
                                    0.25320970042
                                                    0.83505154639175
494248
           0.1
                 0.58064516129032
                                    0.05064194008
                                                    1.83505154639175
359337
           0.1
                 0.51612903225806
                                    0.10199714693
                                                    1.14432989690721
178143
           0.1
                 0.43548387096774
                                    0.13052781740
                                                    0.88659793814432
503153
           0.1
                 0.58064516129032
                                    0.18188302425
                                                    1.31958762886597
426179
           0.1
                 0.61290322580645
                                    0.09557774607
                                                    0.83505154639175
154097
           0.3
                 0.54838709677419
                                    0.11840228245
                                                    1.14432989690721
59076
           0.1
                 0.66129032258064
                                    0.23609129814
                                                    1.02061855670103
28763
           0.1
                 0.74193548387096
                                    0.21398002853
                                                    1.21649484536082
           0.1
72786
                 0.66129032258064
                                    0.13266761768
                                                    1.08247422680412
10182
           0.1
                 0.56451612903225
                                    0.13980028530
                                                    1.32989690721649
           0.2
                 0.46774193548387
                                                    0.97938144329896
486280
                                    0.26105563480
153755
           0.2
                 0.56451612903225
                                    0.22467902995
                                                    0.92783505154639
476383
           0.1
                 0.53225806451612
                                    0.27888730385
                                                    1.19587628865979
365230
           0.1
                 0.500000000000000
                                    0.06847360912
                                                    0.95876288659793
348758
           0.1
                 0.59677419354838
                                                    1.52577319587628
                                    0.08844507845
220536
           0.1
                 0.61290322580645
                                    0.28174037089
                                                    0.84536082474226
97003
                                    0.10199714693
                                                    1.05154639175257
           0.1
                 0.74193548387096
199997
           0.1
                 0.59677419354838
                                    0.12838801711
                                                    0.86597938144329
260303
           0.1
                 0.51483870967741
                                    0.13409415121
                                                    1.10309278350515
           0.1
                                                    1.08247422680412
356829
                 0.51483870967741
                                    0.19044222539
288482
           0.1
                 0.59677419354838
                                    0.10413694721
                                                    1.06185567010309
                 0.53225806451612
           0.1
                                    0.08559201141
                                                    0.84536082474226
132024
            . . .
. . .
                                               . . .
                 0.46451612903225
                                                    0.89690721649484
59471
           0.1
                                    0.11840228245
510602
           0.3
                 0.62903225806451
                                    0.13266761768
                                                    1.51546391752577
490487
           0.1
                 0.66129032258064
                                    0.04850213980
                                                    1.02061855670103
273793
           0.1
                 0.67741935483870
                                    0.16262482168
                                                    1.35051546391752
37768
           0.1
                 0.56451612903225
                                    0.17332382310
                                                    0.98969072164948
307681
           0.3
                 0.57935483870967
                                    0.12910128388
                                                    0.97938144329896
490969
           0.1
                 0.54838709677419
                                    0.21897289586
                                                    1.50515463917525
           0.1
                 0.45161290322580
                                    0.07631954350
                                                    0.90721649484536
438287
451014
           0.1
                 0.61290322580645
                                    0.24322396576
                                                    1.30927835051546
77098
           0.1
                 0.62903225806451
                                    0.23038516405
                                                    1.08247422680412
           0.1
                 0.48387096774193
                                    0.12696148359
                                                    1.04123711340206
80431
112225
           0.1
                 0.53225806451612
                                    0.04707560627
                                                    0.91752577319587
85348
           0.1
                 0.45161290322580
                                    0.07132667617
                                                    1.01030927835051
192473
           0.1
                 0.62903225806451
                                    0.08059914407
                                                    1.02061855670103
348204
           0.1
                 0.51612903225806
                                    0.17617689015
                                                    0.89690721649484
162088
           0.1
                 0.51612903225806
                                    0.21683309557
                                                    0.90721649484536
140724
           0.1
                 0.54838709677419
                                    0.25534950071
                                                    1.13402061855670
362894
           0.1
                 0.37096774193548
                                    0.15905848787
                                                    0.87628865979381
306627
           0.1
                 0.58064516129032
                                    0.25820256776
                                                    0.88659793814432
183737
           0.1
                 0.46774193548387
                                    0.05777460770
                                                    0.86597938144329
490581
           0.1
                 0.48387096774193
                                    0.21326676176
                                                    0.97938144329896
409211
           0.3
                 0.61290322580645
                                    0.19900142653
                                                    0.97938144329896
70446
           0.1
                 0.58064516129032
                                                    0.89690721649484
                                    0.11626248216
69467
           0.1
                 0.56451612903225
                                    0.26676176890
                                                    0.95876288659793
275809
           0.1
                 0.53225806451612
                                    0.26390870185
                                                    0.96907216494845
506799
           0.1
                 0.69354838709677
                                    0.08273894436
                                                    0.83505154639175
425744
           0.2
                 0.54838709677419
                                    0.23537803138
                                                    0.92783505154639
65258
           0.1
                 0.74193548387096
                                    0.12054208273
                                                    1.01030927835051
           0.1
                                    0.09129814550
                                                    0.87628865979381
343146
                 0.46451612903225
```

 $383516 \qquad 0.1 \quad 0.51612903225806 \quad 0.17831669044 \quad 1.09278350515463$

	numborroworo	oroditoooro
65599	numborrowers 0.333333	creditscore 0.916865
467918	0.166667	0.779097
89298	0.166667	0.809976
158714	0.333333	0.813539
313647	0.333333	0.951306
5718	0.333333	0.956057
286298	0.166667	0.945368
395366	0.166667	0.901425
494248	0.166667	0.960808
359337	0.166667	0.956057
178143	0.333333	0.763658
503153	0.333333	0.823040
426179	0.333333	0.863420
154097	0.166667	0.944181
59076	0.166667	0.921615
	0.333333	0.777910
28763		
72786 10182	0.333333 0.166667	0.722090 0.951306
486280	0.166667	0.895487
153755	0.333333	0.951306
476383	0.166667	0.824228
365230	0.166667	0.903800
348758	0.333333	0.954869
220536	0.333333	0.925178
97003	0.333333	0.767221
199997	0.166667	0.923990
260303	0.166667	0.931116
356829	0.166667	0.758907
288482	0.333333	0.824228
132024	0.166667	0.909739
59471	0.166667	0.941805
510602	0.333333	0.901425
490487	0.333333	0.833729
273793	0.166667	0.785036
37768	0.333333	0.858670
307681	0.166667	0.948931
490969	0.166667	0.834917
438287	0.166667	0.802850
451014	0.333333	0.846793
77098	0.333333	0.811164
80431	0.166667	0.954869
112225	0.166667	0.875297
85348	0.166667	0.874109
192473	0.166667	0.818290
348204	0.333333	0.959620
162088	0.333333	0.940618
140724	0.333333	0.762470
362894	0.333333	0.802850
306627	0.166667	0.946556
183737	0.333333	0.953682
490581	9 166667	A 91A926

```
409211
               0.333333
                             0.888361
  70446
               0.166667
                             0.845606
  69467
               0.333333
                             0.875297
  275809
               0.333333
                             0.942993
  506799
               0.166667
                             0.904988
  425744
               0.333333
                             0.959620
  65258
               0.333333
                             0.768409
  343146
               0.333333
                             0.891924
  383516
               0.166667
                             0.823040
  [411093 rows x 6 columns]>
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.65)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[402353
                 0]
      8740
                 0]]
 def loanofficer(Z):
   return (classifier.predict(Z)>.65)
function we will use for "production deployment"
 loanofficer(X.head(2))
  array([[False],
          [False]])
```

need test data - have we just memorized the input data?

try a multiple output final stage? more layers? more cowbell?

testing

creating input features and target variables

```
X= testpdf.iloc[:,1:8]
y= testpdf.iloc[:,0]
X.head()
```

	channel	intrate	loanamt	loan2val	numborrowers	creditscore	loc.
0	0.1	0.500000000000000	0.06633380884	1.08247422680412	0.166667	0.624703	3.0
2	0.1	0.69354838709677	0.29172610556	0.90721649484536	0.166667	0.828979	12.
8	0.1	0.51612903225806	0.09700427960	0.96907216494845	0.166667	0.808789	0.0
9	0.1	0.64516129032258	0.17118402282	1.11340206185567	0.333333	0.948931	18.
13	0.1	0.500000000000000	0.15121255349	0.96907216494845	0.333333	0.942993	5.0

y.head()

```
0
      1
2
8
      0
9
      a
13
Name: label, dtype: int8
eval_model=classifier.evaluate(X, y)
ValueError: Error when checking input: expected dense_7_input to have shape (6,) but go
ValueErrorTraceback (most recent call last)
in engine
---> 1 eval_model=classifier.evaluate(X, y)
/home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training.pyc in evaluate(sel
   1347
                    х, у,
   1348
                    sample_weight=sample_weight,
-> 1349
                    batch_size=batch_size)
                # Prepare inputs, delegate logic to `test_loop`.
   1350
                if self._uses_dynamic_learning_phase():
   1351
/home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training.pyc in _standardize
    577
                    feed_input_shapes,
    578
                    check_batch_axis=False, # Don't enforce the batch size.
--> 579
                    exception_prefix='input')
    580
    581
                if y is not None:
/home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training_utils.pyc in standa
                                     ': expected ' + names[i] + ' to have shape ' +
    143
                                     str(shape) + ' but got array with shape ' +
    144
--> 145
                                     str(data_shape))
            return data
    146
    147
ValueError: Error when checking input: expected dense_7_input to have shape (6,) but go
y_pred=classifier.predict(X)
ValueError: Error when checking input: expected dense_7_input to have shape (6,) but go
ValueErrorTraceback (most recent call last)
in engine
----> 1 y_pred=classifier.predict(X)
/home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training.pyc in predict(self
   1439
   1440
                # Case 2: Symbolic tensors or Numpy array-like.
-> 1441
                x, _, _ = self._standardize_user_data(x)
                if self.stateful:
   1442
   1443
                    if x[0].shape[0] > batch_size and x[0].shape[0] % batch_size != 0:
/home/cdsw/.local/lib/python2.7/site-packages/keras/engine/training.pyc in _standardize
    577
                     feed_input_shapes,
    578
                    check_batch_axis=False, # Don't enforce the batch size.
                     evention profix-'input')
```

[2202

0]]

y_pred=classifier.predict(X)

 $y_pred = (y_pred>0.5)$

```
confusion matrix - barely correct when true
```

```
from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[100571
                0]
   [ 2202
                011
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.4)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[100571
                01
   [ 2202
                0]]
 eval_model=classifier.evaluate(X, y)
  102773/102773 [=========== ] - 6s 62us/step
 eval_model
 [0.09580370603132549, 0.9785741567611694]
 y_pred=classifier.predict(X)
 y_pred = (y_pred > 0.3)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[100571
                0]
     2202
                0]]
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.2)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[100571
                01
   [ 2202
                0]]
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.1)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
```

```
cm = contusion_matrix(y, y_pred)
 print(cm)
  [[100539
                32]
                 4]]
   [ 2198
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.05)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[95479
           5092]
   [ 1776
             426]]
```

creating input features and target variables

```
X= trainpdf.iloc[:,1:7]
y= trainpdf.iloc[:,0]
X.head()
```

	channel	intrate	loanamt	loan2val	numborrowers	creditscore
65599	0.1	0.48387096774193	0.17546362339	0.90721649484536	0.333333	0.916865
467918	0.1	0.59677419354838	0.09914407988	0.86597938144329	0.166667	0.779097
89298	0.1	0.500000000000000	0.21255349500	1.000000000000000	0.166667	0.809976
158714	0.3	0.61290322580645	0.23537803138	1.19587628865979	0.333333	0.813539
313647	0.3	0.54838709677419	0.14835948644	0.86597938144329	0.333333	0.951306

```
y.head()
  65599
             0
  467918
             0
  89298
             0
  158714
             0
  313647
  Name: label, dtype: int8
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.05)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[381260 21093]
   [ 7014
              1726]]
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.1)
confusion matrix - barely correct when true
```

```
from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[402254
                99]
                2211
   8718
 classifier = Sequential()
First Hidden Layer
 classifier.add(Dense(16, activation='relu', kernel_initializer='random_normal', input_d
Second Hidden Layer
 classifier.add(Dense(20, activation='relu', kernel_initializer='random_normal'))
add another layer [[402254 99] [ 8718 22]] to try to beat the above
 classifier.add(Dense(20, activation='relu', kernel_initializer='random_normal'))
Output Layer
 classifier.add(Dense(1, activation='sigmoid', kernel_initializer='random_normal'))
Compiling the neural network
 classifier.compile(optimizer ='adam',loss='binary_crossentropy', metrics =['accuracy'])
tbcallback = tb(log_dir='/tmp/tblog', histogram_freq=0, write_graph=True, write_images=True)
upgrade dask to fix? fork first to save working project !pip install -upgrade -force-reinstall dask tensorboard =
TensorBoard(log_dir="/tmp/tblogs")
```

Fitting the data to the training dataset classifier.fit(X,y, batch_size=10, epochs=50, verbose=1, callbacks=[tbcallbacks] small batch size of 10 is hurting performance moving to 32

```
classifier.fit(X,y, batch_size=32, epochs=10, verbose=1)
```

Epoch 1/10 41 13 14 14 14 15 15 15 16 16 17 17 17 18 18 19 19 19 20 20 20 21 21 21 21 22 22 22 3 24 24 25 25 25 26 26 27 27 27 27 28 28 28 29 29 29 30 30 30 31 31 32 32 32 33 337 34 5 35 35 36 36 36 37 37 37 38 38 38 39 39 40 40 40 41 41 42 42 42 42 42 43 43 43 44 44 4 45 46 46 46 47 47 47 48 48 48 49 49 49 50 50 50 50 51 51 51 52 52 52 53 53 53 53 54 54 5 55 55 56 56 56 57 57 57 58 58 58 58 59 59 59 60 60 60 61 61 61 62 62 62 63 63 63 63 65 65 65 66 66 66 67 67 67 68 68 68 69 69 69 70 70 70 71 71 71 72 72 72 72 73 73 73 4 75 75 75 76 76 76 76 77 77 77 78 78 78 78 79 79 79 80 80 81 81 81 82 82 82 83 83 { 85 85 85 86 86 87 87 87 88 88 88 89 90 90 90 91 91 92 92 92 93 93 94 94 94 95 95 96 7 97 97 98 98 98 99 99 9910010010010010110110210210210310310310410410510510510610616 1071081081081091091091101101111111111112112113113113114114115115115116116116117117117118 191191201201201211211221221221221231231231241241241241251251251261261261271271281281281 913013013013113113113213213213213313313413413513513513613613613713713813813813913913913914 141141142142143143143144144144144145145145146146146146147147147148148148149149149150156 50151151151151151152152152152152152153153153153154154154155155155156156157157157158158159 016016016116116216216216316316316416416416516516516616616616716716716816816916916917017 419519519519619619619619719719719819819919919919920020020020120120120220220320320320426 20520620620620720720720820820820920921021021121121121221221221221321321321421421421521

ss: 0.1028 - accuracy: 0.9787 Epoch 2/10

14 14 14 15 16 16 17 17 17 18 18 19 19 20 21 21 22 22 23 23 24 24 25 25 26 27 27 28 2 30 30 31 31 32 32 33 33 34 34 34 35 35 36 36 37 37 38 38 39 39 40 40 41 41 42 42 43 43 5 45 46 47 47 48 48 49 49 50 50 51 51 52 52 53 54 54 55 55 56 56 56 57 57 57 57 58 58 \$ 60 60 61 61 62 62 62 63 63 64 64 64 65 65 65 66 66 66 67 67 67 68 68 69 69 70 70 70 71 2 73 73 74 74 75 75 76 77 77 78 78 79 79 80 80 81 81 82 83 83 84 84 85 85 86 86 87 87 8 89 89 90 91 91 91 92 92 93 93 94 94 95 96 96 97 97 98 98 99 991001001001011011021021021 2252252252262262272272282282292292302302302312312322323323423423523523623623723723823{ 34334434434534634634734734834834935035035135135235235335335435435535535635635735735835{ Epoch 3/10

13 14 14 15 15 16 16 17 17 18 18 19 20 20 21 21 22 22 23 23 24 25 25 25 26 26 27 28 2 30 31 31 32 32 33 34 34 35 35 36 36 37 37 38 38 39 39 40 41 41 42 42 43 43 44 45 45 46 8 48 49 49 50 50 51 51 52 52 52 53 53 54 54 55 55 56 57 57 58 58 59 59 60 60 61 62 62 64 65 66 66 67 68 68 69 69 70 71 71 71 72 72 73 73 74 74 75 76 76 77 77 78 79 79 80 80 2 82 83 83 84 84 85 85 86 86 87 87 88 88 89 90 90 91 91 92 92 93 94 94 95 95 96 96 97 99100101101102102103103104105105106106107107108109109110110111111111111131131141141151151 711711811811911912012012112112212212312312412412512612612712712812912913013013113213215 1351351351351351351561561561571571581591591601601611611621621631631641641651661661671671681681

7 - accuracy: 0.9787

Epoch 4/10

13 14 14 15 15 16 17 17 18 18 19 19 20 21 21 22 22 23 23 24 24 25 26 26 27 27 28 29 2 31 32 32 32 33 34 34 35 35 36 36 37 37 38 38 39 39 40 40 41 41 42 42 43 43 44 45 45 46 8 48 49 50 50 51 52 52 53 54 54 55 55 56 57 57 58 58 59 60 60 61 62 62 63 63 64 64 65 (66 67 67 68 68 68 69 69 70 71 71 72 72 73 73 74 74 75 75 76 77 77 78 78 79 79 80 80 81 3 83 84 84 85 86 86 87 87 88 88 89 89 90 90 91 92 92 93 93 94 94 95 96 96 97 97 98 98 9 - loss: 0.0955 - accuracy: 0.9787

Epoch 5/10

 13 14 15 15 16 17 17 18 18 19 20 20 21 21 22 23 23 24 24 24 25 26 26 27 28 28 29 30 3 32 33 34 34 35 35 36 36 37 37 38 38 39 39 40 40 41 41 42 42 43 43 44 44 45 45 46 47 47 9 49 50 51 51 52 52 53 53 54 54 55 56 56 57 58 59 59 60 61 61 62 62 63 64 64 65 65 66 68 69 69 70 70 71 71 72 72 73 73 73 74 75 75 75 76 76 77 78 78 78 79 79 80 81 81 82 82 4 85 85 86 86 87 88 88 89 89 90 90 91 92 92 93 93 94 95 95 96 96 97 97 98464/411093 [== >............

Truncating text at 800000 characters to improve display performance. Increase this limit with the environment variable 'MAX_TEXT_LENGTH'

classifier.summary()

```
Model: "sequential_4"
```

Layer (type)	Output Shape	Param #
dense_10 (Dense)	(None, 16)	112
dense_11 (Dense)	(None, 20)	340
dense_12 (Dense)	(None, 20)	420
dense_13 (Dense)	(None, 1)	21

Total params: 893 Trainable params: 893 Non-trainable params: 0

print(classifier.metrics()

save the classifier to deploy

eval_model

[0.09516230860819683, 0.9787396192550659]

what do the input features look like

X.IICuu					
<body> val \</body>	method	DataFrame.head of	channel	intrate	loanamt
65599	0.1	0.48387096774193	0.17546362339	0.90721649484536	
467918			0.09914407988	0.86597938144329	
89298	0.1	0.500000000000000	0.21255349500	1.000000000000000	
158714			0.23537803138	1.19587628865979	
313647	0.3		0.14835948644	0.86597938144329	
5718	0.3		0.21968616262	0.90721649484536	
286298	0.2	0.53225806451612	0.14122681883	1.65979381443298	
395366	0.1	0.500000000000000	0.25320970042	0.83505154639175	
494248	0.1	0.58064516129032	0.05064194008	1.83505154639175	
359337		0.51612903225806	0.10199714693	1.14432989690721	
178143	0.1	0.43548387096774	0.13052781740	0.88659793814432	
503153	0.1	0.58064516129032	0.18188302425	1.31958762886597	
426179	0.1	0.61290322580645	0.09557774607	0.83505154639175	
154097	0.1		0.11840228245	1.14432989690721	
59076	0.3	0.66129032258064	0.23609129814	1.02061855670103	
28763	0.1	0.74193548387096	0.21398002853	1.21649484536082	
72786	0.1	0.66129032258064	0.13266761768	1.08247422680412	
10182	0.1	0.56451612903225	0.13980028530	1.32989690721649	
486280	0.1		0.26105563480	0.97938144329896	
153755	0.2		0.22467902995	0.92783505154639	
476383	0.2		0.27888730385	1.19587628865979	
		0.53225806451612 0.500000000000000			
365230 348758	0.1	0.59677419354838	0.06847360912 0.08844507845	0.95876288659793 1.52577319587628	
	0.1				
220536	0.1	0.61290322580645	0.28174037089	0.84536082474226	
97003	0.1	0.74193548387096	0.10199714693	1.05154639175257	
199997		0.59677419354838	0.12838801711	0.86597938144329	
260303	0.1	0.51483870967741	0.13409415121	1.10309278350515	
356829	0.1	0.51483870967741	0.19044222539	1.08247422680412	
288482	0.1	0.59677419354838	0.10413694721	1.06185567010309	
132024	0.1	0.53225806451612	0.08559201141	0.84536082474226	
59471	0.1		0.11840228245	0.89690721649484	
510602	0.3	0.62903225806451	0.13266761768	1.51546391752577	
490487	0.1	0.66129032258064	0.04850213980	1.02061855670103	
273793	0.1	0.67741935483870	0.16262482168	1.35051546391752	
37768	0.1	0.56451612903225	0.17332382310	0.98969072164948	
307681	0.3	0.57935483870967	0.12910128388	0.97938144329896	
490969	0.1		0.21897289586	1.50515463917525	
438287	0.1	0.45161290322580	0.07631954350	0.90721649484536	
451014	0.1	0.61290322580645	0.24322396576	1.30927835051546	
77098	0.1	0.62903225806451	0.23038516405	1.08247422680412	
80431	0.1	0.48387096774193	0.12696148359	1.04123711340206	
112225	0.1	0.53225806451612	0.04707560627	0.91752577319587	
85348	0.1	0.45161290322580	0.07132667617	1.01030927835051	
192473	0.1	0.62903225806451	0.08059914407	1.02061855670103	
348204	0.1	0.51612903225806	0.17617689015	0.89690721649484	
162088	0.1	0.51612903225806	0.21683309557	0.90721649484536	
140724	0.1	0.54838709677419	0.25534950071	1.13402061855670	
362894	0.1	0.37096774193548	0.15905848787	0.87628865979381	
306627		0.58064516129032	0.25820256776	0.88659793814432	
183737	0.1	0.46774193548387	0.05777460770	0.86597938144329	

112225

0.166667

```
490581
            0.1
                 0.4838/096//4193
                                    0.213266/61/6
                                                     0.9/938144329896
409211
            0.3
                 0.61290322580645
                                    0.19900142653
                                                     0.97938144329896
70446
            0.1
                 0.58064516129032
                                    0.11626248216
                                                     0.89690721649484
69467
            0.1
                 0.56451612903225
                                    0.26676176890
                                                     0.95876288659793
275809
            0.1
                 0.53225806451612
                                    0.26390870185
                                                     0.96907216494845
            0.1
506799
                 0.69354838709677
                                    0.08273894436
                                                     0.83505154639175
            0.2
                 0.54838709677419
425744
                                    0.23537803138
                                                     0.92783505154639
            0.1
65258
                 0.74193548387096
                                    0.12054208273
                                                     1.01030927835051
343146
            0.1
                 0.46451612903225
                                    0.09129814550
                                                     0.87628865979381
383516
            0.1
                 0.51612903225806
                                    0.17831669044
                                                     1.09278350515463
        numborrowers
                       creditscore
65599
             0.333333
                           0.916865
467918
                           0.779097
             0.166667
89298
             0.166667
                           0.809976
158714
             0.333333
                           0.813539
313647
             0.333333
                           0.951306
5718
             0.333333
                           0.956057
286298
             0.166667
                           0.945368
                           0.901425
395366
             0.166667
494248
             0.166667
                           0.960808
359337
             0.166667
                           0.956057
178143
             0.333333
                           0.763658
503153
             0.333333
                           0.823040
426179
             0.333333
                           0.863420
154097
             0.166667
                           0.944181
59076
             0.166667
                           0.921615
28763
             0.333333
                           0.777910
72786
             0.333333
                           0.722090
10182
             0.166667
                           0.951306
486280
             0.166667
                           0.895487
153755
             0.333333
                           0.951306
476383
             0.166667
                           0.824228
365230
             0.166667
                           0.903800
348758
             0.333333
                           0.954869
220536
             0.333333
                           0.925178
97003
             0.333333
                           0.767221
199997
             0.166667
                           0.923990
260303
             0.166667
                           0.931116
356829
             0.166667
                           0.758907
288482
             0.333333
                           0.824228
132024
             0.166667
                           0.909739
. . .
59471
             0.166667
                           0.941805
510602
             0.333333
                           0.901425
490487
             0.333333
                           0.833729
273793
             0.166667
                           0.785036
37768
             0.333333
                           0.858670
             0.166667
                           0.948931
307681
490969
             0.166667
                           0.834917
438287
             0.166667
                           0.802850
451014
                           0.846793
             0.333333
77098
             0.333333
                           0.811164
80431
             0.166667
                           0.954869
```

0.875297

```
85348
                             0.874109
               0.166667
  192473
               0.166667
                             0.818290
                             0.959620
  348204
               0.333333
  162088
               0.333333
                             0.940618
  140724
               0.333333
                             0.762470
  362894
               0.333333
                             0.802850
  306627
               0.166667
                             0.946556
  183737
               0.333333
                             0.953682
  490581
               0.166667
                             0.910926
  409211
               0.333333
                             0.888361
  70446
               0.166667
                             0.845606
  69467
               0.333333
                             0.875297
  275809
               0.333333
                             0.942993
  506799
               0.166667
                             0.904988
  425744
               0.333333
                             0.959620
  65258
               0.333333
                             0.768409
  343146
               0.333333
                             0.891924
  383516
               0.166667
                             0.823040
  [411093 rows x 6 columns]>
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.1)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[402353
                 01
                 0]]
      8740
 def loanofficer(Z):
    return (classifier.predict(Z)>.65)
function we will use for "production deployment"
 loanofficer(X.head(2))
  array([[False],
          [False]])
```

need test data - have we just memorized the input data?

try a multiple output final stage? more layers? more cowbell?

testing

creating input features and target variables

```
X= testpdf.iloc[:,1:7]
y= testpdf.iloc[:,0]
X.head()
```

	channel	intrate	loanamt	loan2val	numborrowers	creditscore
Λ	Λ 1	0.500000000000000	0 06622200004	1 00047400600410	0 166667	0 604700

U	U. I	ບ.ວບບບບບບບບບບບ	U.U003338U884	1.0024/422000412	U.10000/	U.024/U3
2	0.1	0.69354838709677	0.29172610556	0.90721649484536	0.166667	0.828979
8	0.1	0.51612903225806	0.09700427960	0.96907216494845	0.166667	0.808789
9	0.1	0.64516129032258	0.17118402282	1.11340206185567	0.333333	0.948931
13	0.1	0.500000000000000	0.15121255349	0.96907216494845	0.333333	0.942993

```
y.head()
  0
        1
  2
  8
  9
  13
  Name: label, dtype: int8
 eval_model=classifier.evaluate(X, y)
  eval_model
 [0.09564311794400045, 0.9785741567611694]
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.1)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[100571
                0]
   [ 2202
                0]]
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.05)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[89422 11149]
   [ 1450
           752]]
 y_pred=classifier.predict(X)
 y_pred = (y_pred>0.07)
confusion matrix - barely correct when true
 from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y, y_pred)
 print(cm)
  [[97586
           2985]
   [ 1917
            28511
```

رردن

Console will exit automatically if it remains idle for another sixty seconds. Engine exited with status 129.