Santander

Product Recommendation

Team 7 | Vaishali, Nishant, Arpit

04/23/2018

1 Goals

2 Project Set Up

3 Data Modelling

4 Testing

5 User Interface

6 Summary

Prof. Robin Hillyard

Academic semester- Spring 2018

CSYE 7200 Big Data System Engineering with Scala

Goals

- Learn and enhance skills on Scala programming, Apache Spark, Data Analysis
- Meet deadlines of each sprint and activities associated with it
- Collaborative learning and knowledge sharing, to have good team work
- Sharpen presentation skills in a group
- Achieve the stated acceptance criteria

Acceptance Criteria

Use Cases

Approach

Timeline

Acceptance Criteria

- Precision for Predictive model will be approx. 0.55

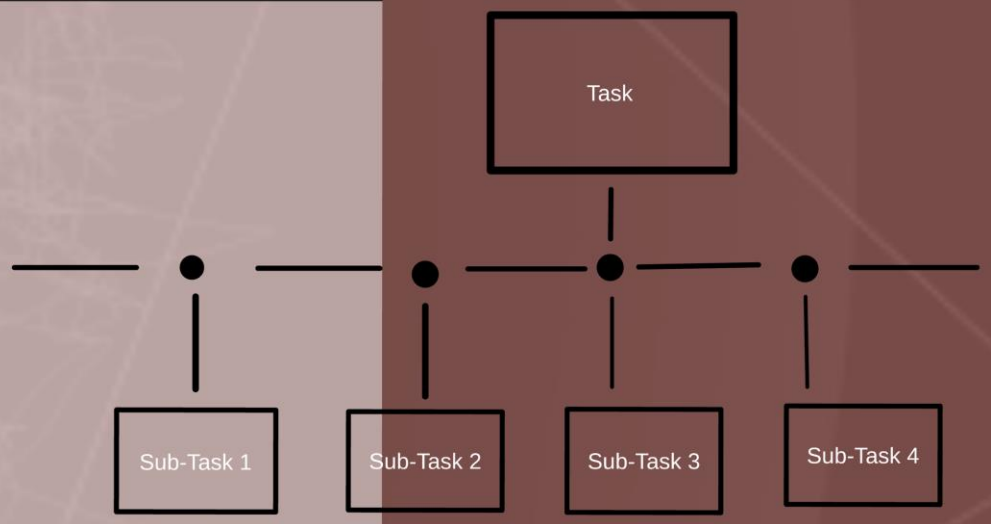
Use Cases

Actor – Customer

- **As a new customer [customer for less than 6 months], customer will see top rated banking products**
- **As an existing customer [customer for more than 6 months], customer will see recommendation for relevant products on the basis of previous months product consumption of a customer**

Approach

Divide Task in Multiple Sub- Tasks



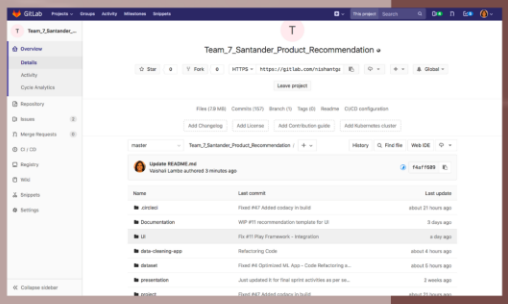
Timeline

Sprint#	Timeline	Tasks
Sprint 1	03/19/2018 - 03/25/2018	Environment Set Up, Data Cleaning, Data Visualization, Unit Test Cases, Testing
Sprint 2	03/26/2018 - 04/01/2018	ML Spark, Data Modelling, Integration with pipeline, Testing
Sprint 3	04/02/2018 - 04/08/2018	Model fitting and cross validation, Testing,
Sprint 4	04/09/2018 - 04/15/2018	Optimization, UI framework integration
Sprint 5	04/16/2018 – 04/22/2018	Re-Testing and finishing, Preparation of Final Presentation

2 Project Set Up

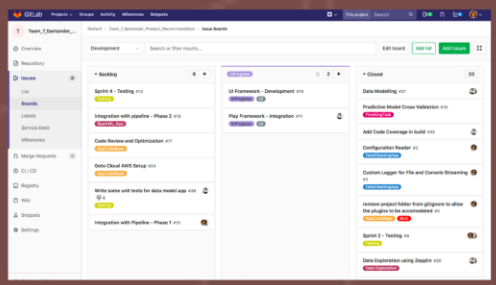
- Repository Set Up
- IntelliJIDEA
- Zeppelin
- Play Framework

Repository Set Up

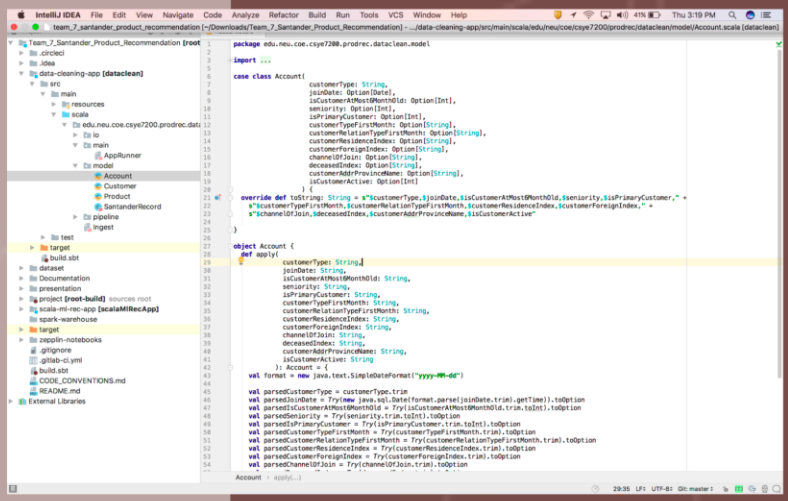


Repository View

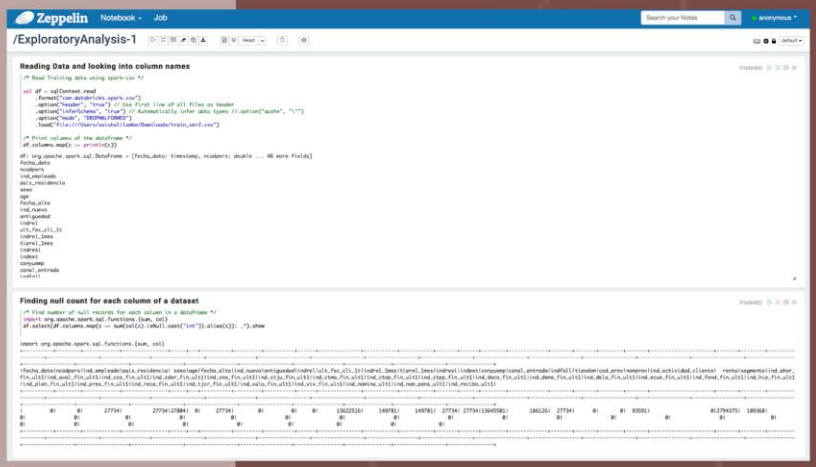
Issue Board



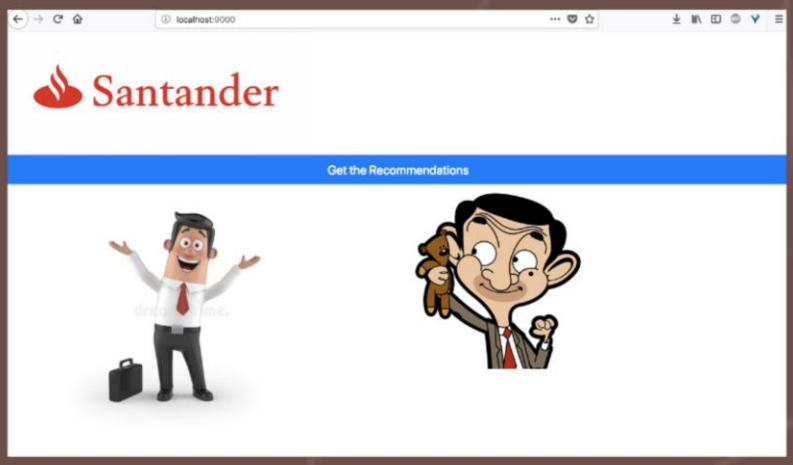
IntelliJ IDEA



Zeppelin



Play Framework



3 Data Modelling

Exploratory Analysis

Data Cleaning

Modelling

Exploratory Analysis

Data Source:
https://www.kaggle.com/c/santander-product-recommendation/data

Data Size: ~2.3GB [1.36M rows]

Some Observations

- All columns names are in Spanish which need to convert in English
- Total 15 columns have Null values [Details and approach to handle it is in Repository/ Documentation folder]
- Number of Female Customers [46%] are less than Number of Male customers [54%]
- Last Date being Primary Customer the max value is 2016-05-30
- Individual Customers [58%] are more than VIP [6%] and Students [36%] of total number of customers
- Customer type has values of data type String Double and Integer
- Average gross income of VIP customers is more than Individual and Student customers
- Average gross income of female is lesser than male
- Count of Guarantees is maximum for male individual type customers with average gross income approx. 139593
- Further analysis shows that all the products are consumed maximum by male individual type of customer
- There are more university students as customer than other types [Individual and VIP]
- The Madrid region has maximum number of customers
- Number of customers as per their Join date [First_Date_Acc_Holder] is nearly steady for initial 6 months span of a year

Screenshots of plots/charts

Customer distribution as per last date being primary customer

Regionwise Distribution of Customers

Num_Guarantees	Num_Gender	Cust_Gender	Num_Cust_Identification	Cust_Identification	Avg_Gross_Income
2659949	3659949	V	3659949	02 - PARTICULARES	139593.5396594424
2589984	2589984	H	2589984	02 - PARTICULARES	141557.2471155884
2121150	2121150	H	2121150	03 - UNIVERSITARIO	113415.91116352427
1672298	1672298	V	1672298	03 - UNIVERSITARIO	120236.61854936828
308160	308160	V	308160	01 - TOP	173018.6541929042
173815	173815	H	173815	01 - TOP	182649.58602367855

Products consumtption as per customer and their gross income, gener, identification

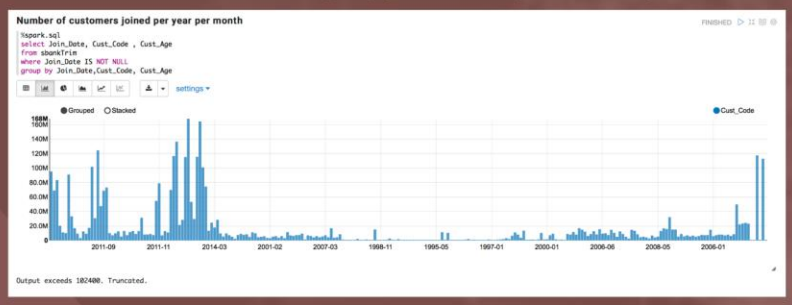
Avg_Gross_Income	Cust_Identification
175853.08854550548	01 - TOP
141558.18551324733	02 - PARTICULARES
116431.558391003	03 - UNIVERSITARIO

Average Gross income across customer identification

Customer distribution as per gender

Limitations of zeppelin

- Data Visualization is limited [zeppelin.interpreter.output.limit 102400]



[Total imported data was 1.36M rows out of which zeppelin can visualize only 102K, that means 10% of data is visualized]

- Performance issue [very slow with scala,spark and sql interpreter], compare to jupyter notebook zeppelin in quite unstable.

Data Cleaning

Approach:

- Try to make use of Best Practices

```
object Pipeline {

  def run(input: String, ss: SparkSession): DataFrame = {
    import ss.implicits._

    /* Parsing */
    val stringDS = DataParser.getStringDS(input, ss)
    val classDS = DataParser.stringDStoClassDS(stringDS, ss)

    /* Filtering */
    var classDS1 = classDS.filter(d => d.customerInfo.code != None)
      .filter(d => d.productInfo.product != "[]")
      .filter(d => d.accountInfo.seniority.getOrElse(0) >= 0)
      .map(d => if (d.customerInfo.age.getOrElse(0) > 100) {
        new SantanderRecord(
          Customer(d.customerInfo.code,
            d.customerInfo.employmentStatus,
            d.customerInfo.countryOfResidence,
            d.customerInfo.gender,
            None,
            d.customerInfo.income),
          d.accountInfo,
          d.productInfo
          )
      } else d )

    /* Transformation */
    var df = TransfomationLogic.classDStoDF(classDS1)
    df = TransfomationLogic.replaceEmptyToUnknown(df)
    df = TransfomationLogic.replaceEmptyToRation(df)
    df = TransfomationLogic.replaceNullWithAvg(df)
    df = TransfomationLogic.fixAge(df)

    /* Format */
    df = TransfomationLogic.formatColumnDF(df)

    df
  }
}
```

Parsing
↓
Filtering
↓
Transformation
↓
Format

DataModel

```scala
case class SantanderRecord(customerInfo: Customer, accountInfo: Account, productInfo: Product)
```

```scala
case class Customer(
        code: Option[Int],
        employmentStatus: String,
        countryOfResidence: String,
        gender: String,
        age: Option[Int],
        income: Option[Double]
        )
```

```scala
case class Product(product: String)
```

```scala
case class Account(
                    customerType: Option[String],
                    joinDate: Option[Date],
                    isCustomerAtMost6MonthOld: Option[Int],
                    seniority: Option[Int],
                    isPrimaryCustomer: Option[Int],
                    customerTypeFirstMonth: Option[String],
                    customerRelationTypeFirstMonth: Option[String],
                    customerResidenceIndex: Option[String],
                    customerForeignIndex: Option[String],
                    channelOfJoin: Option[String],
                    deceasedIndex: Option[String],
                    customerAddrProvinceName: Option[String],
                    isCustomerActive: Option[Int]
                  )
```

Approach: CommandLine Parsing

https://github.com/scopt/scopt

"com.github.scopt" %% "scopt" % "3.7.0"

```scala
case class Config(input: Option[String] = None, output: Option[String] = None)

object AppRunner extends Serializable {

  def main(args: Array[String]) {

    val parser = new scopt.OptionParser[Config]("DataCleaningApp")
    {
      head("Data Cleaning App", "1.0")
      opt[String]('i', "input") required() action
        { (x, c) => c.copy(input = Some(x)) } text("input is the input path")
      opt[String]('o', "output") required() action
        { (x, c) => c.copy(output = Some(x)) } text("output is the output path")
    }

    parser.parse(args, Config()) match {
      case Some(config) =>
        val input = config.input.get
        val output = config.output.get

        val ss = SparkSession
          .builder()
          .appName("Data Cleaning App")
          .master("local[*]")
          .config("spark.debug.maxToStringFields",100)
          .getOrCreate()

        ss.conf.getAll.foreach(println)

        val resultdf = Pipeline.run(input, ss)

        resultdf.coalesce(1).write.option("header","true").csv(output)

      case None =>
    }

  }
}
```

Approach: Reading CSV

Problem Statement:
How to ignore comma (,) inside quoted (") string while spliting csv line? The regex with only comma does not work here.
example:

name,address
nishant,"Boston, MA"
Arpit,"Boston"
Vaishali,"Cambridge Ave"

```
val splitRow = input.split("""",(?=([^\"]*\"[^\"]*\")*[^\"]*$)""")
```

Approach: Testing Spark Transformation

https://github.com/holdenk/spark-testing-base

"com.holdenkarau" %% "spark-testing-base" % "2.2.0_0.9.0" % "test",

```
it should "work for Transformation" in {

  val sqlCx = sqlContext
  import sqlCx.implicits._

  val input1 = sc.parallelize(Seq(Some(10),Some(20),Some(30),None)).toDF(Seq("age"): _*)
  val expectedOutput1 = sc.parallelize(Seq(10,20,30,20)).toDF(Seq("age"): _*)
  val actualOutput1 = TransfomationLogic.fixAge(input1)
  assertDataFrameEquals(expectedOutput1, actualOutput1)

  val input2 = sc.parallelize(Seq(Some(10.0),Some(20.0),Some(30.0),None)).toDF(Seq("income"): _*)
  val expectedOutput2 = sc.parallelize(Seq(10.0,20.0,30.0,20.0)).toDF(Seq("income"): _*)
  val actualOutput2 = TransfomationLogic.replaceNullWithAvg(input2)
  assertDataFrameEquals(expectedOutput2, actualOutput2)

}
```

Challenges: Dataset Transformation

Problem Statement:

How to do Transformation operation on Dataset[SomeComplexObject] when SomeComplexObject is made of non-primitive datatype members?

```
var classDS1 = classDS.filter(d => d.customerInfo.code != None)
  .filter(d => d.productInfo.product != "[]")
  .filter(d => d.accountInfo.seniority.getOrElse(0) >= 0)
  .map(d => if (d.customerInfo.age.getOrElse(0) > 100) {
    new SantanderRecord(
      Customer(d.customerInfo.code,
        d.customerInfo.employmentStatus,
        d.customerInfo.countryOfResidence,
        d.customerInfo.gender,
        None,
        d.customerInfo.income),
      d.accountInfo,
      d.productInfo
    )
  } else d )
```

Challenges: Dataset to DataFrame

Problem Statement:

How to convert Dataset[SomeComplexObject] in flat DataFrame, where flat DataFrame requires more than 22 columns?

Limitation of Existing Solution:

- Every solution on the internet talks about two step proces.
  - Step one: Convert Dataset into tupple,
  - Step two: Use tupple to create DataFrame
- The solution is not applicable when the DataFrame has more than 22 columns, because as of now Scala 2.11 has only Tuple1 to Tuple22.

```
val custCol = Seq("code", "employmentStatus", "countryOfResidence", "gender", "age", "income")
for (x <- custCol) {
  df = df.withColumn(x, col("customerInfo")(x))
}
df = df.drop(col("customerInfo"))

val accCol = Seq("customerType", "joinDate", "isCustomerAtMost6MonthOld", "seniority", "isPrimaryCustomer",
  "customerTypeFirstMonth", "customerRelationTypeFirstMonth", "customerResidenceIndex", "customerForeignIndex",
  "channelOfJoin", "deceasedIndex", "customerAddrProvinceName", "isCustomerActive")
for (x <- accCol) {
  df = df.withColumn(x, col("accountInfo")(x))
}
df = df.drop(col("accountInfo"))

df = df.withColumn("product", col("productInfo")("product"))
df = df.drop(col("productInfo"))
df
```

Ref: https://underscore.io/blog/posts/2016/10/11/twenty-two.html

Challenges: Spark Testing

Problem Statement:

- Creating **input** DataFrame with null in Column Values
- Creating **expectedOutput** DataFrame that does not has null in Column Values
- Compare result of **actualOutput** with **expectedOutput** DataFrame without **SchemaMismatch error**

Failed Solution Approch 1:

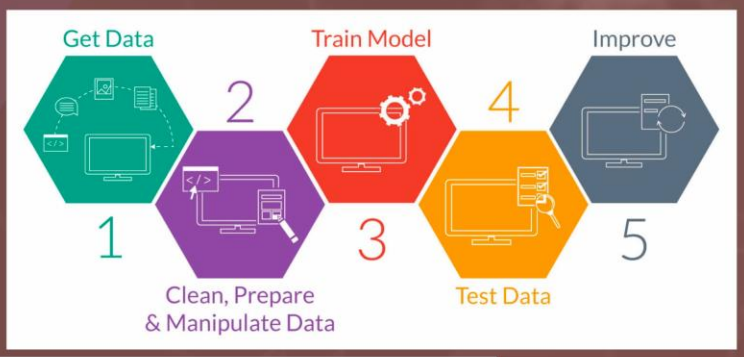
- Use DataFrameGenerator from "com.holdenkarau" %% "spark-testing-base"
- Defining own schema using "StructType" and "StructField" where you have option to make column nullable.
- You can not pass Seq of dataset with None/null. Integer datatype does not support that.

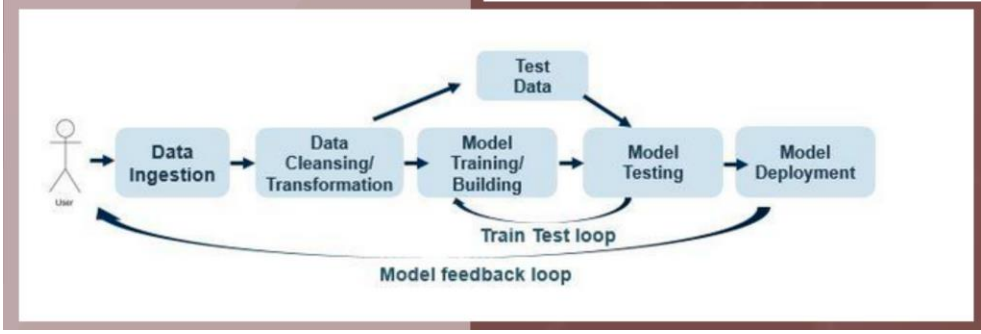
Failed Solution Approch 2:

- Use native spark library to create dataframe with Option[Integer].
- The DataFrame encoder does not understand Option[Integer]/Some[Integer]

```
val input1 = sc.parallelize(Seq(Some(10),Some(20),Some(30),None)).toDF(Seq("age"): _*)
val expectedOutput1 = sc.parallelize(Seq(10,20,30,20)).toDF(Seq("age"): _*)
val actualOutput1 = TransfomationLogic.fixAge(input1)
assertDataFrameEquals(expectedOutput1, actualOutput1)
```

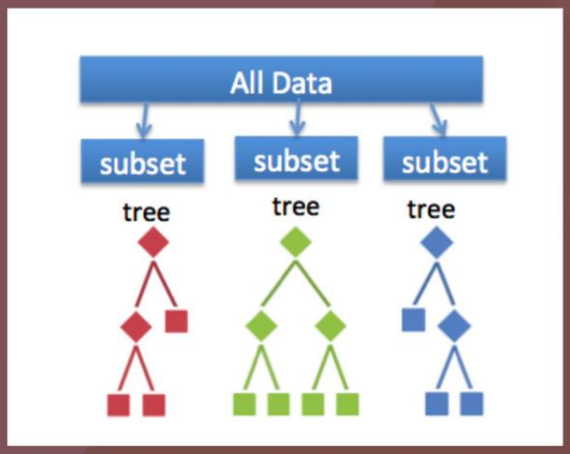
Data Modelling





Model Selection

2 1 3



Greedy

Overfittiing

Decision Tree

VS.

Random Forest

A random forest takes a random subset of features from the data, and creates n random trees from each subset. Trees are aggregated together at end.

Pipeline

Load Clean Data → Filter Data → Indexing Categorical Features → Split Train/ Test Data (70% - 30%) → Converting Features to Vector (Transformer) → Building/ Fitting Model → Saving Model → Making Prediction for Test Data → Evaluating Model → Saving Predictions

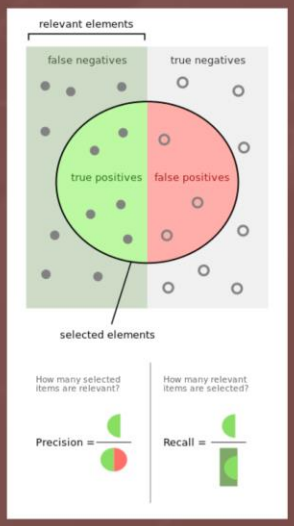
Model Evaluation Metric

predictedLabel	Features
[3]	[1013024.0,23.0,3...
[3]	[1013038.0,38.0,4...
[3]	[1013064.0,56.0,7...
[3]	[1013080.0,36.0,1...
[3]	[1013116.0,50.0,1...
[3]	(9,[0,1,2,5],[101...
[3]	[1013166.0,23.0,3...
[3]	[1013169.0,31.0,1...
[3]	[1013171.0,68.0,9...
[6]	[1013173.0,7.0,95...
[3]	[1013176.0,27.0,4...
[3]	[1013177.0,25.0,1...
[3]	(9,[0,1,2,5],[101...
[3]	(9,[0,1,2,5],[101...
[3]	(9,[0,1,2,5],[101...
[3]	(9,[0,1,2],[10131...
[3]	[1013198.0,27.0,7...
[3]	[1013204.0,26.0,1...
[3]	[1013215.0,29.0,8...
[3]	[1013235.0,44.0,1...

Precision - 0.63

```
18/04/22 11:54:29 INFO DAGScheduler: Job 44 finished: collec
18/04/22 11:54:29 INFO org: Precision = 0.6303460983226195
18/04/22 11:54:30 INFO SQLHadoopMapReduceCommitProtocol: Usi
```

Correct positive predictions



Challenges

- Amount of data
- Features Selection
- Tuning Random Forest Model
- Handling categorical features
- Testing Apache spark code
- Gradient Boosted Trees do not yet support multiclass classification

```
import org.scalatest.{FlatSpec, Matchers}
import org.apache.spark.sql.SparkSession

trait SparkSessionTestWrapper {

  lazy val spark: SparkSession = {
    SparkSession
      .builder()
      .master("local")
      .appName("Spark Data Model App Test")
      .getOrCreate()
  }

}

class AppSpec extends FlatSpec with SparkSess

  behavior of "load data method"
```

```
package edu.neu.coe.csye7200.prodrec.learning

import org.apache.log4j.Logger
import org.apache.spark.sql.{DataFrame, SparkSession}
import org.joda.time.{DateTime, Seconds}
import org.apache.spark.ml.classification.RandomForestClassifier
import org.apache.spark.ml.feature.{IndexToString, StringIndexer, Stri
import org.apache.spark.ml.Pipeline
import org.apache.spark.ml.evaluation.MulticlassClassificationEvaluato
//import org.apache.spark.ml.classification.NaiveBayes
//import org.apache.spark.ml.classification.DecisionTreeClassifier

object DataModelApp extends App {

  val SANTANDER_PRODUCT_RECOMMENDATION_APP = "Santander Product Recomme
  val SET_UP_MESSAGE_COMPLETION = "Spark Set Up Complete"
  val CREATE_MODEL_MESSAGE = "Creating Random Forest Model"
  val SAVE_MODEL_MESSAGE = "Saving the Model"
  val CREATE_PIPELINE_MESSAGE = "Creating Pipleline"

  val filePath = "./dataset/clean_data.csv"
  val modelSavePath = "./dataset/spark-random-forest-model"
  val maxBin:Int = 60
  val splitSeed:Int = 5043
  val metricName = "weightedPrecision"
  val featuresColName = "Features"
  val productColName = "product"
  val productIndexedColName = "productIndexed"
  val predictColName = "prediction"
  val predictOutputColName = "predictedLabel"

  val numericColNames:Seq[String] = Seq("code","age","income")
  val categoricalColNames:Seq[String] = Seq(
    "gender",
    "employmentStatus",
    "customerAddrProvinceName",
    "customerRelationTypeFirstMonth",
    "customerType",
    "deceasedIndex"
  )

  val logger = getLogger()
```

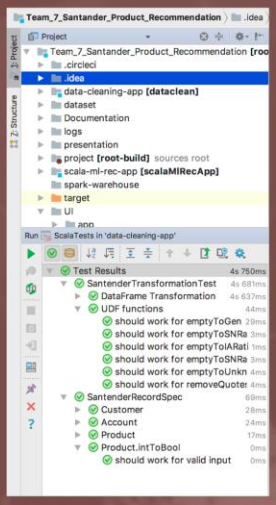
4 Testing

Coverage

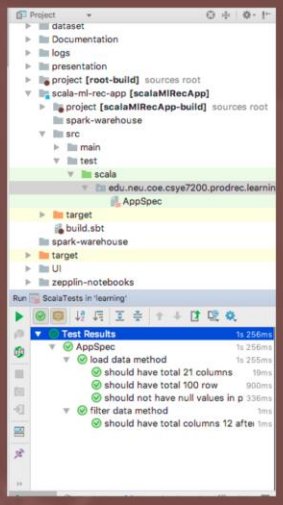
Report

Coverage

Data Transformation & Cleaning



ML App



Coverage Report

43.60%

All packages	43.60%
edu.neu.coe.csye7200.prodrec.dataclean.io	0.00%
edu.neu.coe.csye7200.prodrec.dataclean.main	0.00%
edu.neu.coe.csye7200.prodrec.dataclean.model	88.04%
edu.neu.coe.csye7200.prodrec.dataclean.pipeline	31.82%
edu.neu.coe.csye7200.prodrec.learning	12.07%

SCoverage generated at Sun Apr 22 19:59:44 EDT 2018

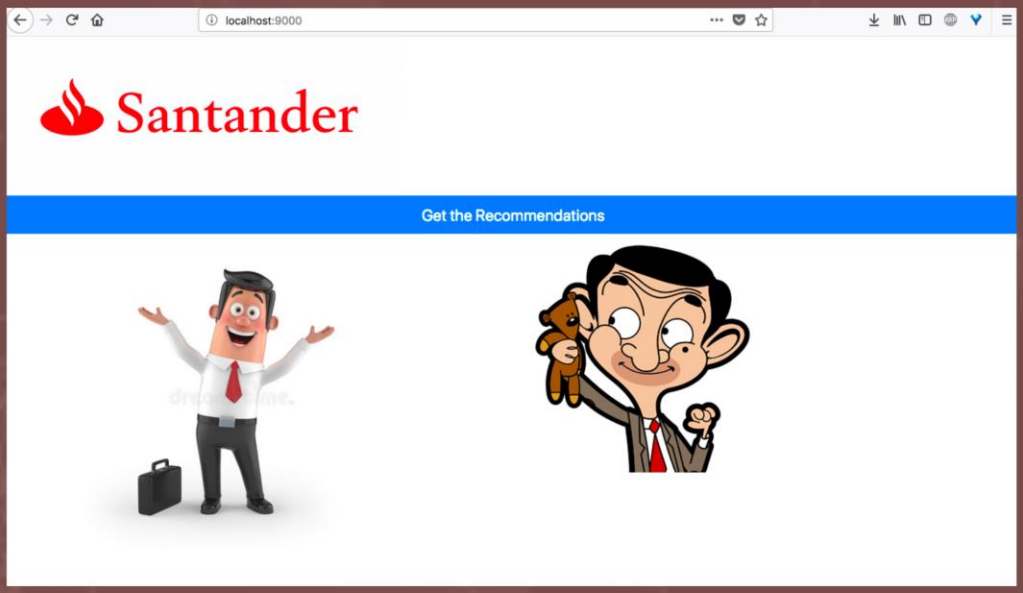
Lines of code:	629	Files:	8	Classes:	8	Methods:	26
Lines per file:	78.62	Packages:	5	Classes per package:	1.60	Methods per class:	3.25
Total statements:	500	Invoked statements:	218	Total branches:	64	Invoked branches:	49
Ignored statements:	0						
Statement coverage:	43.60 %			Branch coverage:	76.56 %		

Class	Source file	Lines	Methods	Statements	Invoked	Coverage	Branches	Invoked	Coverage
DataParser	DataParser.scala	36	2	51	0	0.00 %	0	0	0.00 %
AppRunner	AppRunner.scala	40	1	17	0	0.00 %	0	0	0.00 %
Account	Account.scala	54	1	33	33	100.00 %	0	0	100.00 %
Customer	Customer.scala	36	1	19	19	100.00 %	2	2	100.00 %
Product	Product.scala	73	2	132	110	83.33 %	48	37	77.08 %
Pipeline	Pipeline.scala	41	1	27	0	0.00 %	2	0	0.00 %
TransfomationLogic	TransfomationLogic.scala	133	12	105	42	40.00 %	12	10	83.33 %
DataModelApp	App.scala	216	6	116	14	12.07 %	0	0	100.00 %

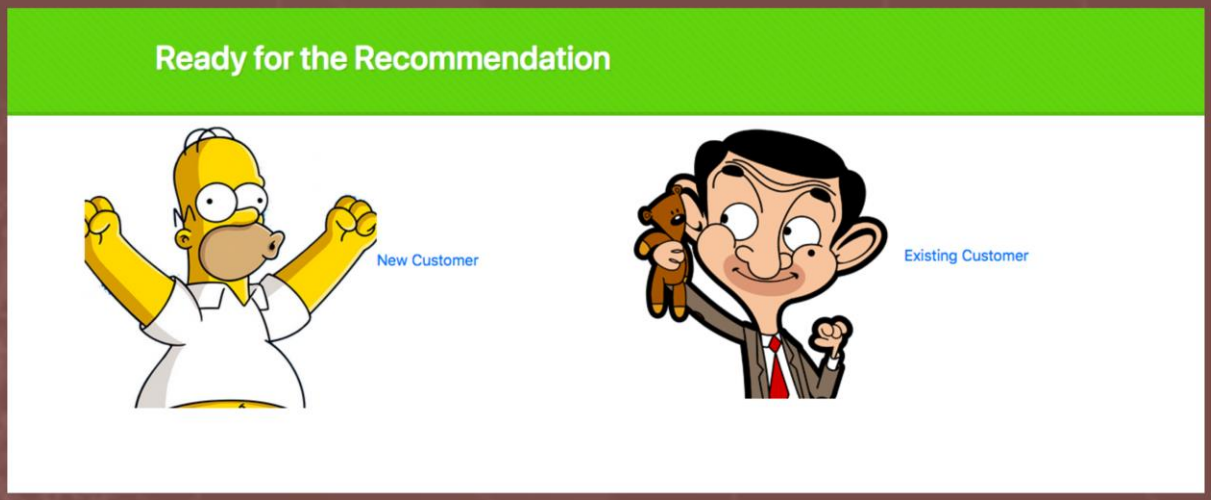
5 User Interface

Screenshots

Homepage



Manager Profile



Existing Customer Page

Recommendations

Customer No. 1050616

Products 3

CURRENT ACC

JUNIOR ACC

CREDIT CARD

New Customer Page

Recommendations

Customer No. 1050610

Products 0

Current Account	Payroll Nom	Direct Debit
Junior Account	Pension Nom	Long Term Deposit

Summary

1 . Met acceptance criteria
Achieved precision is: 0.63 [More than stated in acceptance criteria]

2. Delivered Project On Time

3. Improved Collaborative learning, Knowledge sharing

4. Improved Presentation Skills