

# Enhancing Credit Analysis & Assessment using Geospatial Techniques

By:

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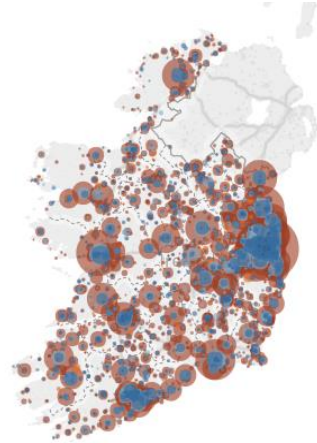
Supervisors:

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Selwyn Hearn, KPMG

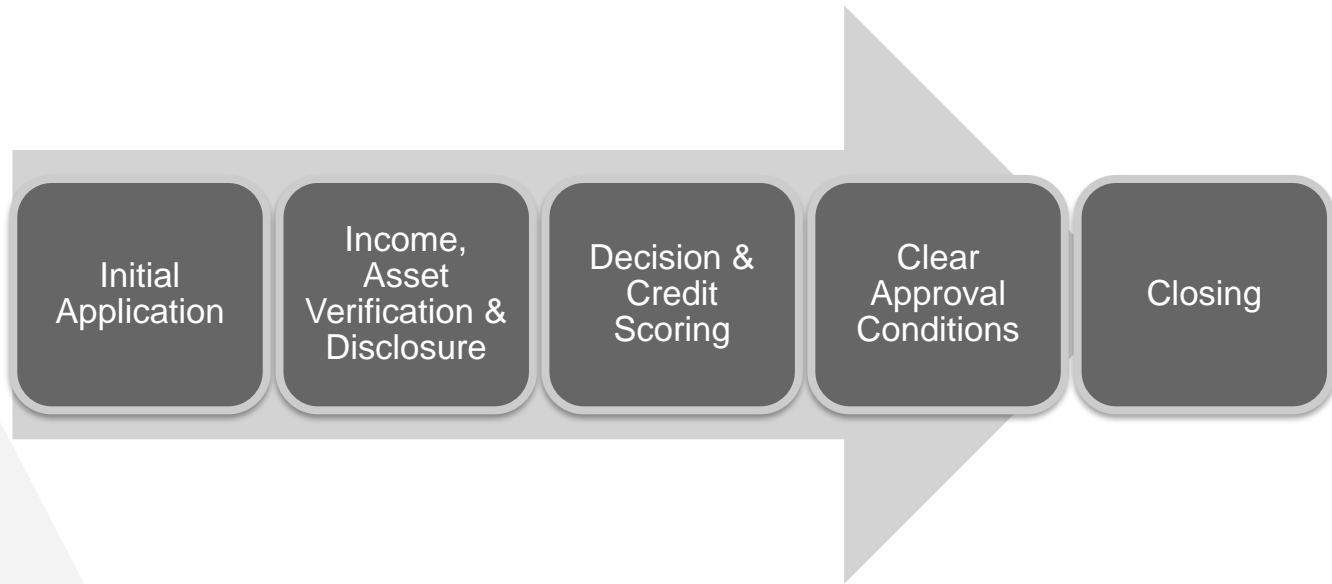


# Business Problem



# 3

## Loan Process





# Previous Work

## Previous Work

Method	Authors
Linear Regression	Lee and Chen (2005); Hand and Henley (1997)
Discriminant Analysis	Fisher (1936); Durand et al. (1941); Altman (1968); Eisenbeis (1978); Zhou et al. (2016); Liberati et al. (2017)
Logistic Regression	Hosmer et al. (1989); Altland (1999); Nie et al. (2011); Abdou et al. (2008); Bensic et al. (2005); Joanes (1993)
Decision trees	Kohavi and Quinlan (2002); Breiman et al. (1984); Zhang et al. (2010); Zekic-Susac et al. (2004); Zhou et al. (2008); Huang et al. (2007); Xia et al. (2017); Koh et al. (2015); Koutanaei et al. (2015)
Neural networks	Demuth et al. (2008); West (2000); Gately (1995); Presky et al. (1996); Ghosh and Reilly (1994); Desai et al. (1996)

## Previous Work

- ▶ Durand et al. (1941) used the Discriminant analysis for modelling a scoring system that gives a prediction about loan repayment.
- ▶ Limitations:
  - ▶ Reduction in dimensionality
  - ▶ Improper estimation of classification error
  - ▶ Using linear functions instead of quadratic function

## Previous Work

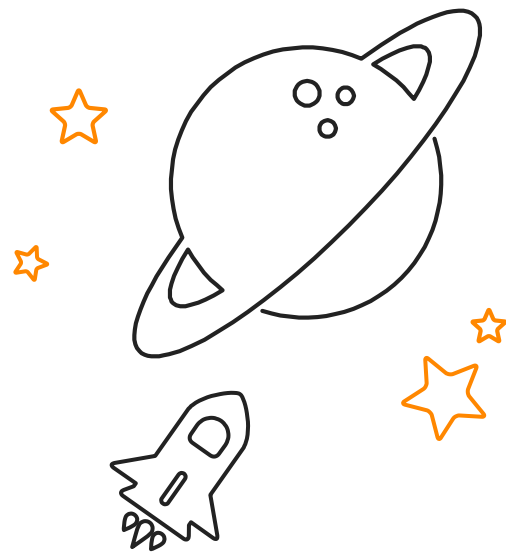
- ▶ Huang et al. (2007) used decision tree along with support vector machines to build credit scoring model
- ▶ Limitations of SVMs:
  - ▶ Long training time
  - ▶ Black box nature of model( similar to NNs)

## Previous Work

- ▶ Carling and Lundberg (2005) combined the geographical information with loan data to examine the credit rationing.
- ▶ Finding:
  - ▶ Technological changes outweigh needs of geographical proximity
  - ▶ Increasing distance between lender and borrower might be alarming



# Methodology



## Data Sources:

- Credit Rating and Loan portfolio from Bank
- Property price register
- Employment Rate(CSO)

## Key Variables:

- DefaultedLoans
- CreditRating
- PropertyValue
- LoanBalance
- LTV
- InterestType
- ProbationaryLoans
- County
- Town
- AddressLatitude
- AddressLongitude

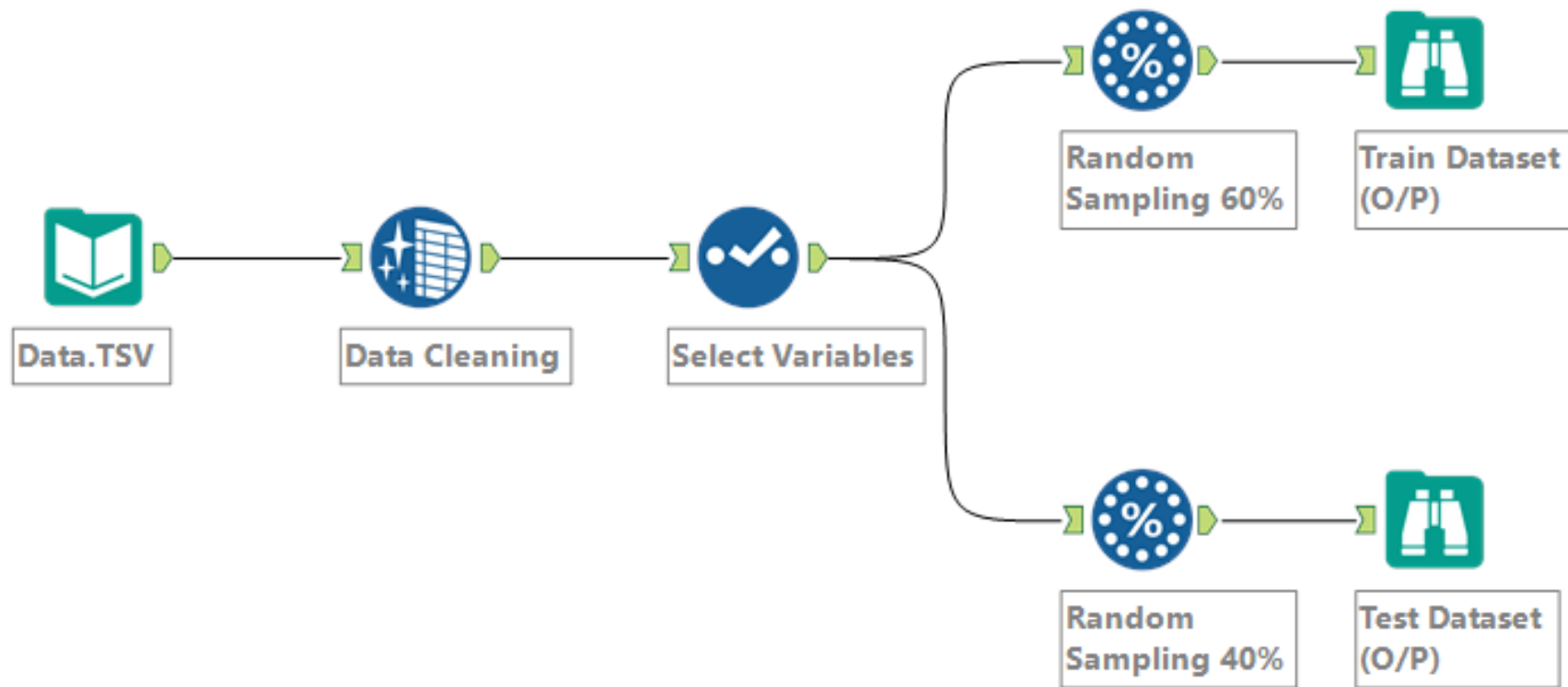
## Data Assumptions

- Geospatial data such as address latitude and address longitude is assumed to depict geospatial location of a property correctly
- Dimensions of house and size of the house(number of rooms, bathrooms, lawn, etc.) are not considered during model development
- Factors such as neighbourhood, amenities etc. are not considered that affects the property price in the market

## Algorithms Considered

- ▶ Logistic Regression
- ▶ Decision Tree(CART)

# Data Processing



# Connecting Tableau with R

Tableau - MAP with City Origin

File Data Worksheet Dashboard Story Analysis Map Format Server Window Help

Analytics

test\_results

Dimensions

- Branch
- Contract Ref
- County
- Defaulted Loans
- In Arrears
- Interest Type
- Last Valuation Date
- LTV Category
- LTVCategoryUpdated
- Maturity Date
- Mortgage Type

Measures

- %\_HousePriceMovem
- Address Latitude
- Address Longitude
- Annual PYMT
- Credit Rating
- Credit Rating Move
- DaysInArrears
- DecisionTree\_Model
- Distance from Origin
- DT score.No

Parameters

- Origin City

Columns: AVG(Address Longit..)

Rows: AVG(Address Latitud..)

Filters: Distance from Ori..

MAP

AGG(Distance from Ori...)

0.00 19.00

Origin City

Carnew, Wicklow

SUM(Loan Balance)

DecisionTree\_Model

Results are computed along Table (across).

```
SCRIPT_REAL('library(rpart);
fit = rpart( DefaultedLoans ~ CreditRating + NewLoan + InterestIncome
+ PropertyValue + County + LTVCategory + LTV + LoanBalance +ContractRef,
method="class", control=rpart.control(minsplit=10, cp=0.001),
data.frame(DefaultedLoans = .arg1, LoanBalance =.arg2, CreditRating=factor(.arg3), NewLoan =
LTVCategory = factor(.arg8), LTV = .arg9, ContractRef =.arg10));
data.frame(predict(prune(fit,0.028), type = "vector"))[1,]',
ATTR([DefaultedLoans]),AVG([Loan Balance]),ATTR([CreditRating]),ATTR([NewLoan]),AVG([Interest
ATTR([County]), ATTR([LTVCategory]),ATTR([LTV]),ATTR([Contract Ref]))]
```

The calculation is valid.

Default Table Calculation

Apply OK

All

Enter search text

- ABS
- ACOS
- AND
- ASCII
- ASIN
- ATAN
- ATAN2
- ATTR
- AVG
- CASE
- CEILING
- CHAR
- COLLECT

Loan Balance

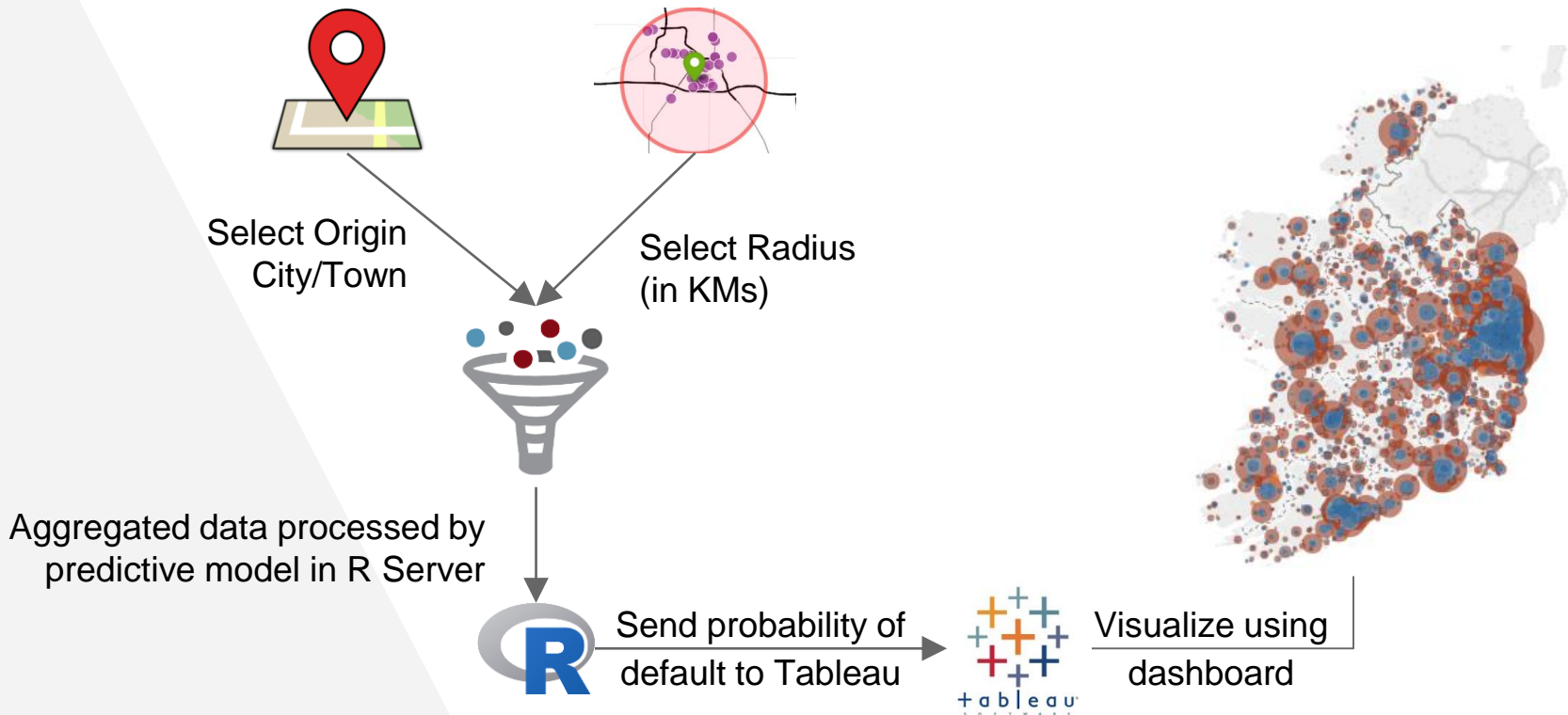
Data type: Float

Describe...

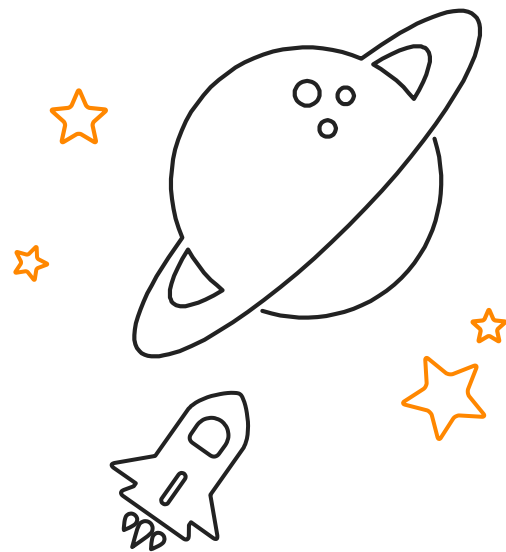
38487 marks 1 row by 1 column SUM of AVG(Address Longitude): -277.453.235

Deepak Gupta

# Our Approach



# Analysis





# Distribution of Loan Accounts

Original Data

## Defaulted Loans

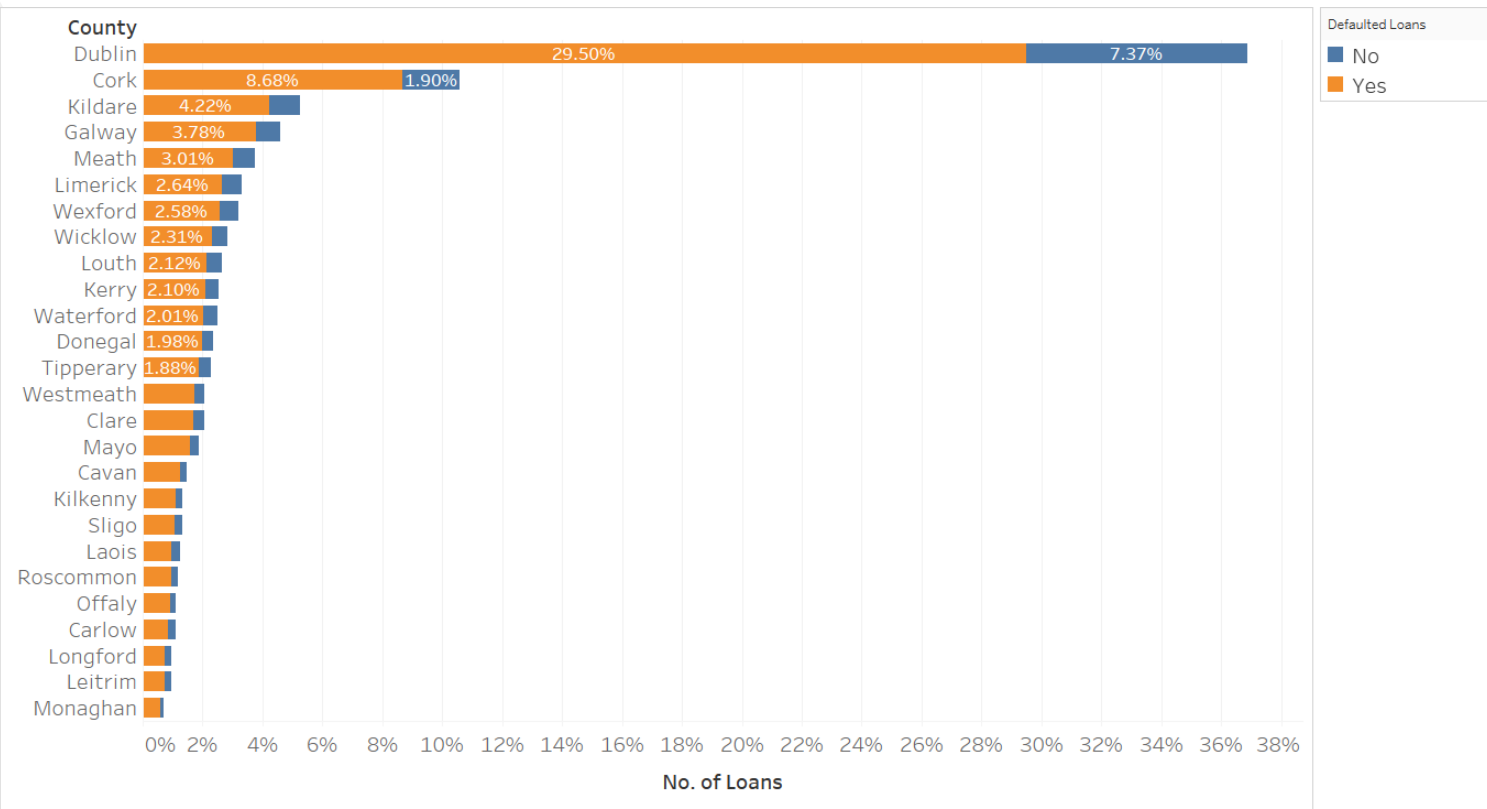
Credit Rating	No	Yes
1	20.33%	
2	20.87%	0.03%
3	17.00%	0.03%
4	13.45%	
5	1.09%	27.19%

Normalized Data

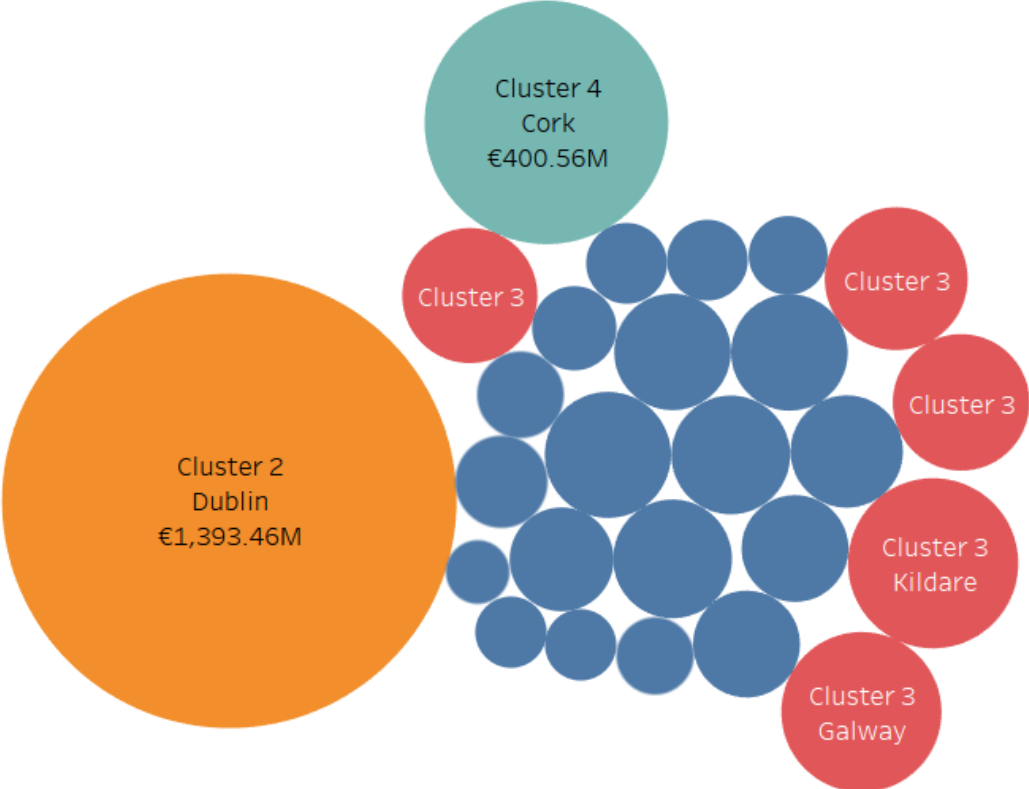
## Defaulted Loans

Credit Rating	No	Yes
1	1.31%	19.02%
2	0.69%	20.21%
3	7.24%	9.79%
4	8.01%	5.44%
5	1.86%	26.42%

# Distribution of Loan Accounts vs County

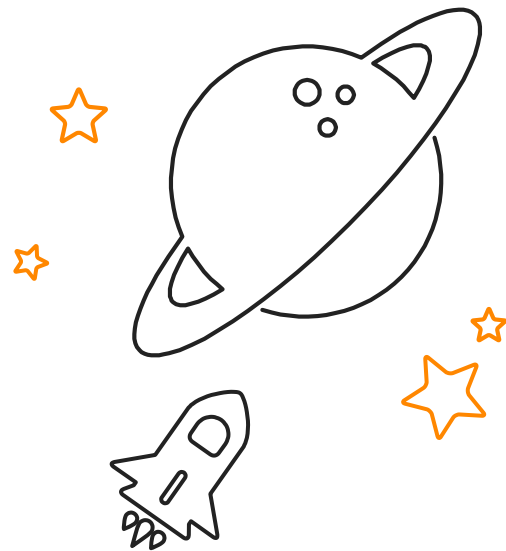


# Clustering County based on Loan Balance



# Results

Logistic Regression and Decision Tree



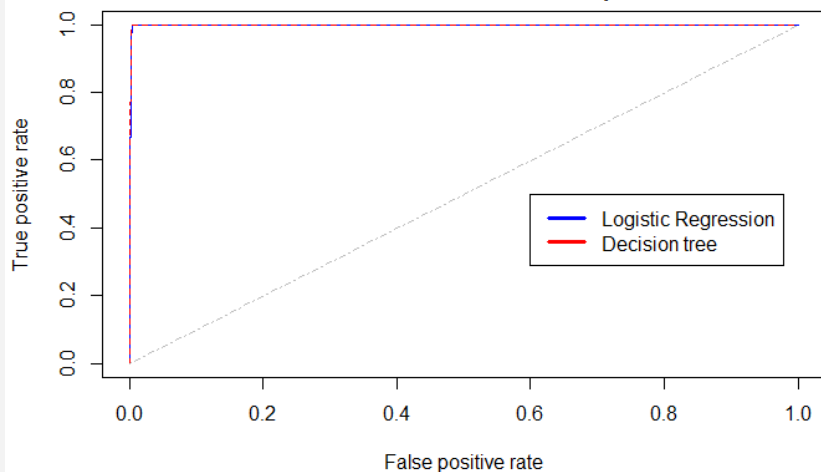
# Model Performance Metrics

	Logistic Regression			Decision Tree		
Data/Measure	AUROC	KS	Gini	AUROC	KS	Gini
Original Data	99.82	15	10	99.72	99.38	99.44
Normalized Data	67.61	24	16	81.4	59.96	62.8

# Model Performance Comparison

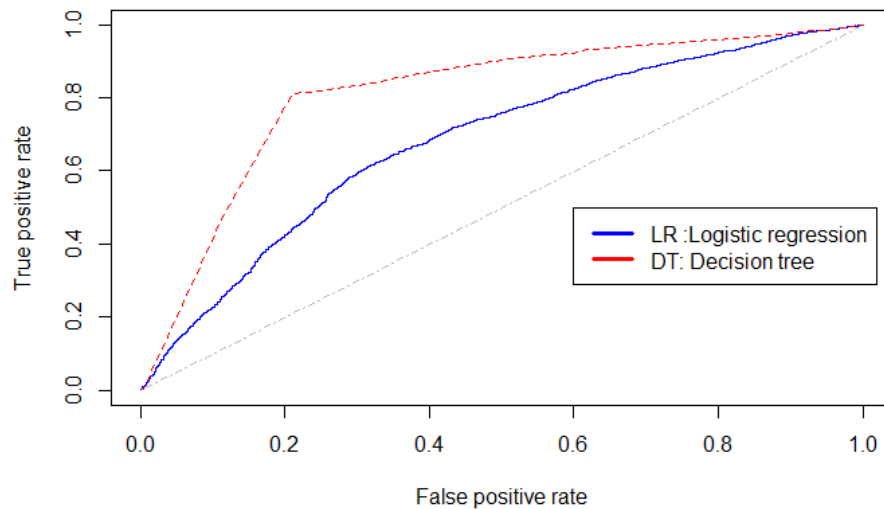
## Original Data

ROC's: Model Performance Comparison

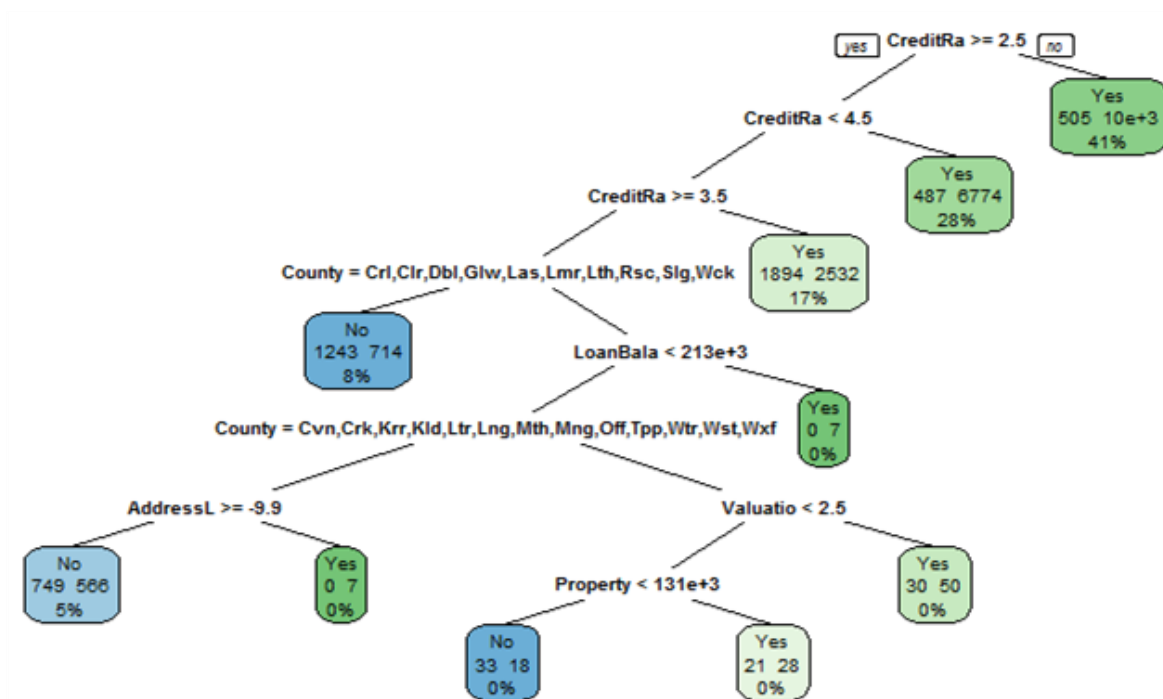


## Normalized Data

ROC's: Model Performance Comparison



# Decision Tree<sup>+</sup>



<sup>+</sup> Limited number of nodes in tree due to page size constraint

# Dashboard Link



## Measure of Success

47%

Auditors feel this dashboard is extremely useful

70% users

Feel that geospatial techniques have enhanced credit assessment

60% users

Likely to recommend this dashboard to colleagues

## End Users Profile<sup>+</sup>

### **Selwyn H**

Head of IRM Audit at KPMG  
Ireland

### **James F**

Auditor, KPMG

### **Simon M**

Head of Data Science, Segmatic

### **John M**

Software Developer, Kinesene  
Ltd

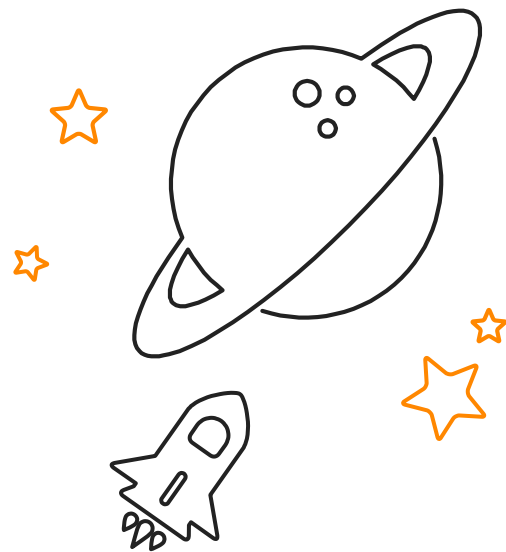
### **Ciaran F**

Senior Product Consultant,  
Tableau

### **John L**

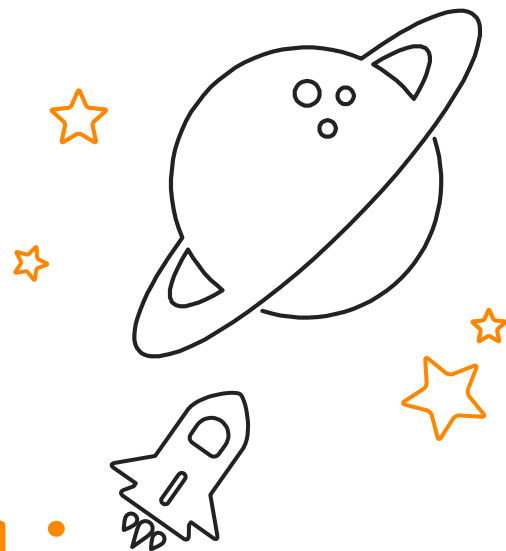
Banking Director, SAS UKI

# Business Contributions



## Business Contributions

- ▶ Interactive way to identify patterns in datasets to drill down into problem areas
- ▶ Well timed potential issues indicators that adhere to provisions of audit processes and assessment of residential loans
- ▶ Better and greater coverage of problem areas and increased focus on judgemental loan applications
- ▶ Integration of useful and relevant market data and economic indicators for enhanced loan assessment



# Recommendations

## Recommendations

### **Dashboard**

Real transactional data can improve the performance of Tableau dashboard which acts as decision support system

### **Geospatial Data**

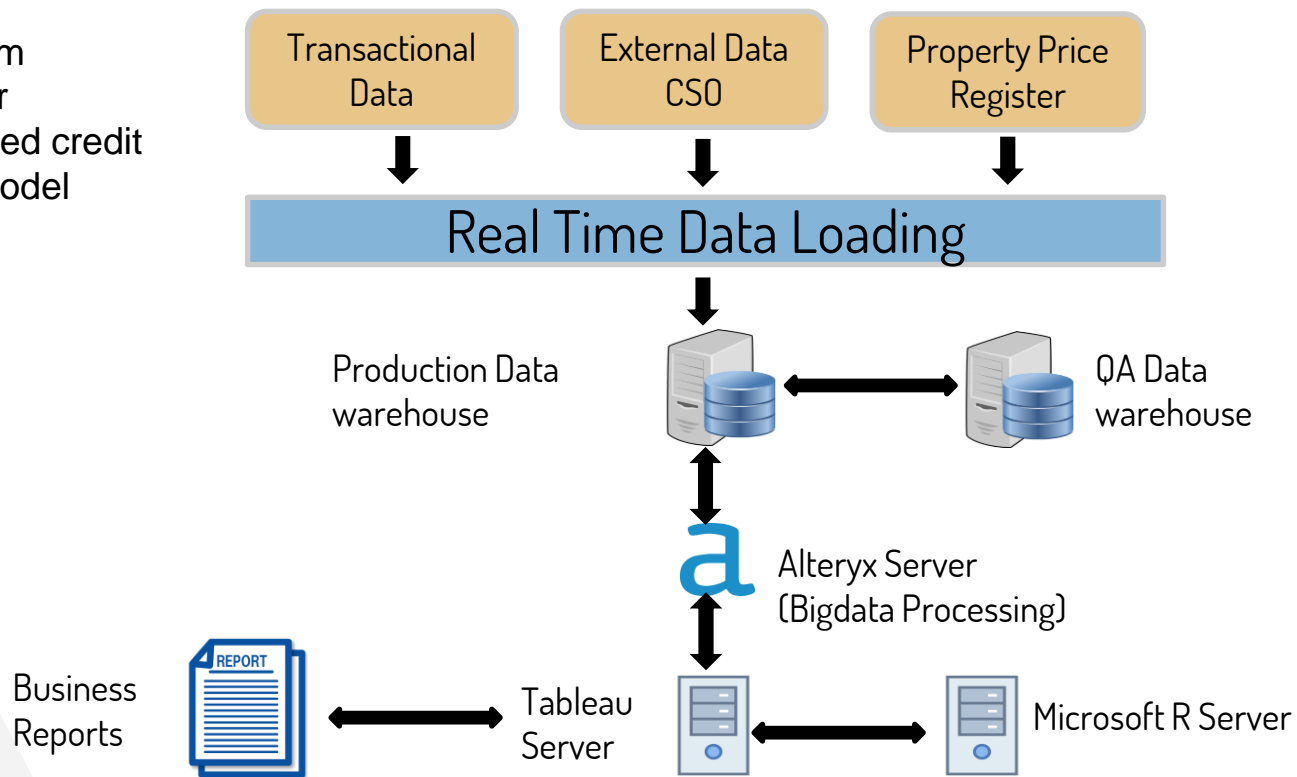
Credit assessment can be enhanced if it includes information such as house coordinates

### **External Factor**

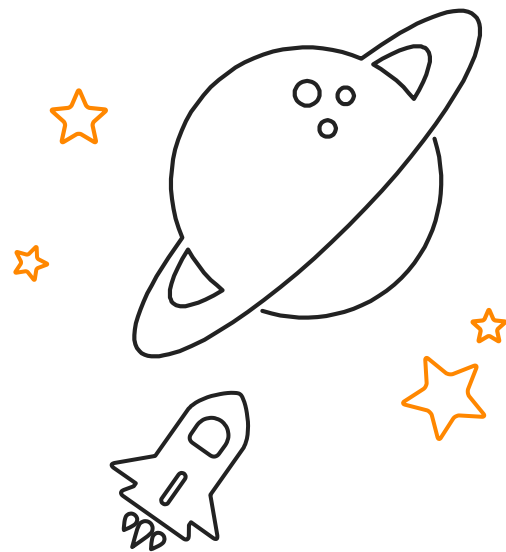
The model can perform better when trained with large number external factors such medical information, average salary in neighbourhood

# Recommendations

Detailed system architecture for geospatial based credit assessment model



# Our Learning



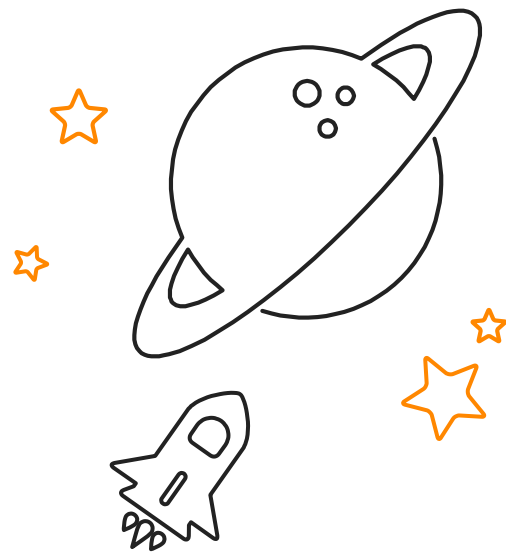




## Our Learning

- ▶ Importance of Data Processing
- ▶ Deployment of RServer
- ▶ How performance of a model can vary with data
- ▶ Human interaction is must in credit analysis

# Conclusion



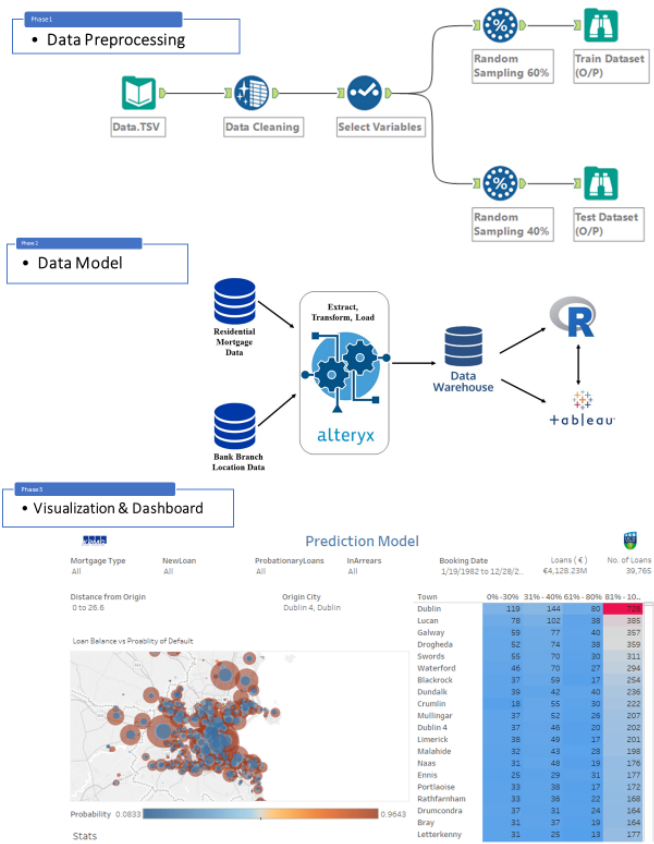


# Enhancing Credit Analysis & Assessment Using Geo-Spatial Techniques



Deepak Kumar Gupta, Shruti Goyal, Supervisor: Prof. Peter Keenan  
MSc Business Analytics ( Practicum)

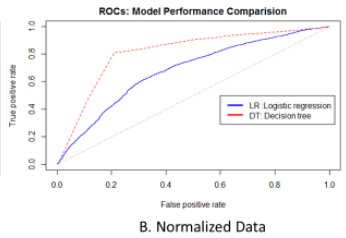
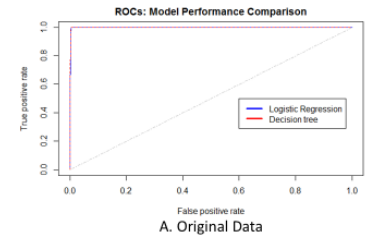
**Problem Statement:** To improve information and underlying data with regard to loan performance, particularly in the property sector using Geo-spatial techniques with interactive dashboard.



## Results:

Model performance evaluated with original data and normalized data on Logistic regression and decision tree. Both model gave accuracy of 99.89% but with normalized dataset, decision tree outperformed logistics regression by 20% better accuracy.

Model	Logistic Regression			Decision Tree		
Data/Measure	AUROC	KS	Gini	AUROC	KS	Gini
Original Data	99.82	99.25	99.64	99.72	99.38	99.44
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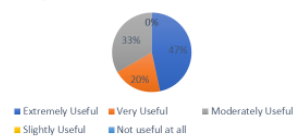


## Business Contributions:

1. Auditors and credit analysts can use the dashboard to identify potential default loans
2. Financial institutions can develop new business strategies to offer loans targeted to particular areas

## Conclusion:

As an auditor, How useful do you think this dashboard is?



- 47% user said this dashboard is extremely useful as auditing tool for loan portfolios.
- Decision tree perform better over logistic regression model
- Algorithm performance can be improved when real transactional data plugs in.