Towards AI

Credit Default Modelling Using Decision Trees

Detecting Credit Worthiness using Tree-based techniques

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Machine Learning Algorithms have historically been used in the Credit and Fraud Space. With the increase in computational power, the Industry has made a move from Tree-based Logit models to more advanced Machine Learning Techniques involving Bagging and Boosting. industry. The article is designed to provide the readers with a Mathematical View of Decision Trees, Bagging, and Random Forest Algorithms. In the final section, the writer

discusses how to use these techniques for Credit Default and Fraud Prevention using Data from LendingClub.

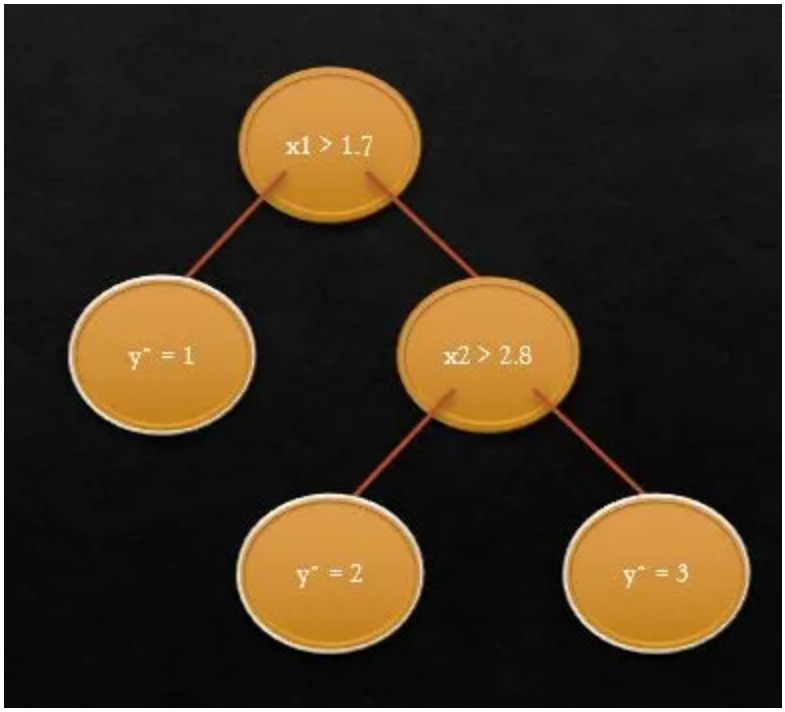
Decision Trees

1. Introduction

The basic intuition behind decision trees is to map out all possible decision paths in the form of a binary tree. Showcasing the same with the example of identifying flower type(y) using the ratio of sepal length to width(x1) and the ratio of petal length to width(x2)

The initial split at x1>1.7 helps in identifying flower type y=1

The next node split at x2>2.8 helps identify y=2 and y=3



Sample Example for Decision Tree

Mathematically, a **Decision Tree** maps inputs **x** ∈ **R^d** to output **y** using binary decision rules:

Each node in the tree has a splitting Rule

- Splitting based on top-down Greedy Algorithm
- Each Leaf Node is associated with an output value

Each splitting rule is of the form

- h(x) = 1{xj > t}

2. Splitting Criteria

Regression Criteria :

- Mean Squared Error : $H(X_m) = \frac{1}{N_m} * \sum_{i \in N_m} (y_i - y_{mean})^2$
- Mean Absolute Error : $H(X_m) = \frac{1}{N_m} * \sum_{i \in N_m} |y_i - y_{mean}|$

Classification Criteria :

- Gini Index : $H(X_m) = \sum_{k \in y} (1 - p_{mk})$
- Cross Entropy : $H(X_m) = \sum_{k \in y} p_{mk} log(p_{mk})$

X_m : Observations in node m

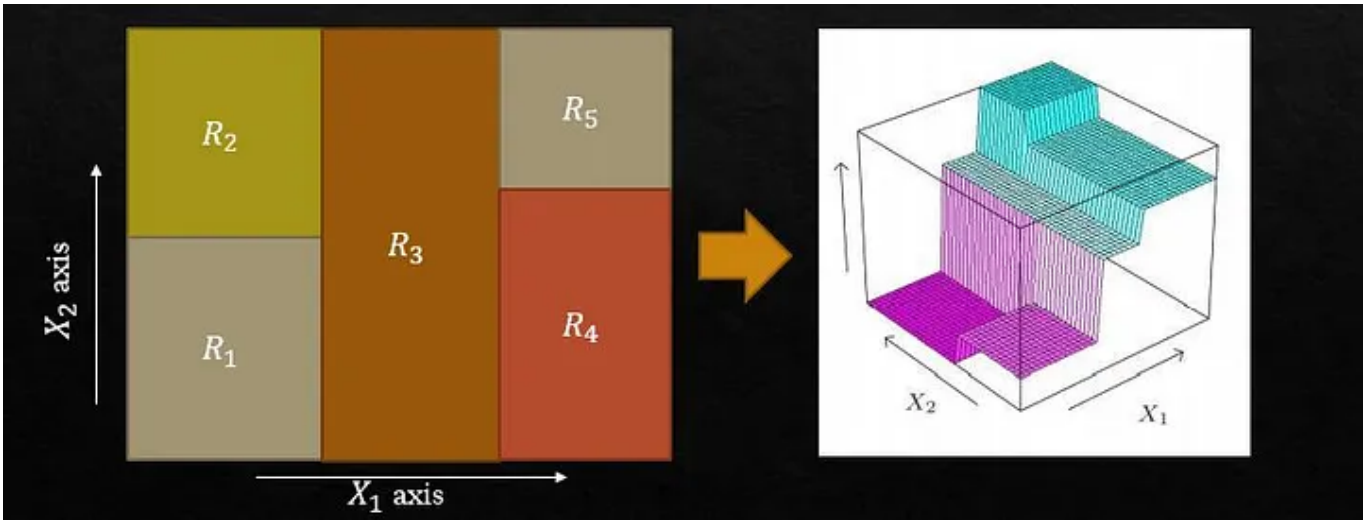
y classes

p_{m*} distribution over classes in node m

3. Geometrical View

Motivation :

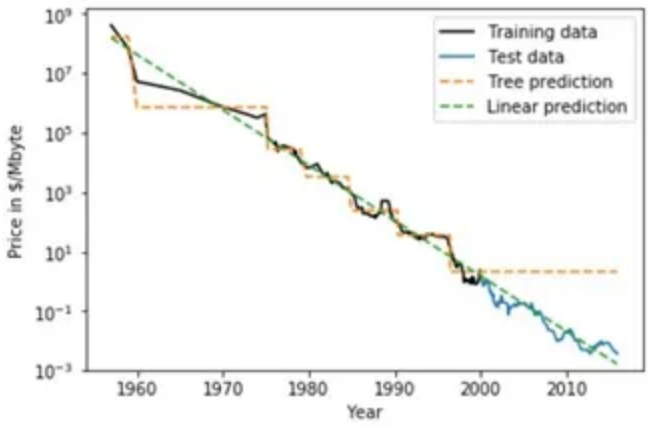
- Partition the space so that data in a region have the same prediction
- Each partition represents a vertical or horizontal line in the 2-D plane



Geometric View for Decision Trees

4. Challenges

- Decision Trees cannot Extrapolate



- High Variance or Instability to change in data: By minor change in data we see the variation in the Structure of the Decision Tree
- The reason for the High Variance in decision trees lies in the fact that they are based on a Greedy Algorithm. It focuses on optimizing for the

node split at hand, rather than taking into account how that split impacts the entire tree. A greedy approach makes Decision Trees run faster but makes them prone to **overfitting**.

In the next sections, we will discuss how to overcome these challenges

Different Ensemble Architectures — Photo by Thomas Griesbeck on Unsplash

Bootstrap Aggregator

1. Motivation

- **Decision Tree** can have **high variance** in them if you use a tree without pruning
- Using Multiple trees can decrease the Variance

Let X_i be an independent and identical distribution

Then $Y = \frac{\sum_{k=1}^{N}(X_i)}{N}$

$$Var(Y) = Var(\frac{\sum_{k=1}^{N}(X_i)}{N}) = \frac{\sum_{k=1}^{N}(Var(X_i))}{N^2}$$

$$Var(Y) = \frac{Var(X_1)}{N}$$

- Bagging or Bootstrap Aggregation is one way of creating $X_i's$

2. Algorithm

1. Generate Bootstrap Samples $B_1, B_2 \ldots\ldots B_b$

   Create B_b by picking points from $x_1, x_2, x_3 \ldots\ldots x_n$ randomly n times

   A particular x_i can appear in B_b many times

2. Generate estimators $f(B_b)$ using data B_b

Random Forest

1. Motivation

- Estimators generated using Bagging Data B_b, i.e $f(B_b)$ might not be highly uncorrelated if the nodal structure is similar
- Using Multiple trees can decrease the Variance

Let X_i be an independent and identical distribution

Then $Y = \frac{\sum_{k=1}^{N}(X_i)}{N}$

$$Var(Y) = Var(\frac{\sum_{k=1}^{N}(X_i)}{N}) = \frac{\sum_{k=1}^{N}(Var(X_i))}{N^2}$$

$$Var(Y) = \frac{Var(X_1)}{N}$$

- Random Forest Algorithm can be used for creating $X_i's$

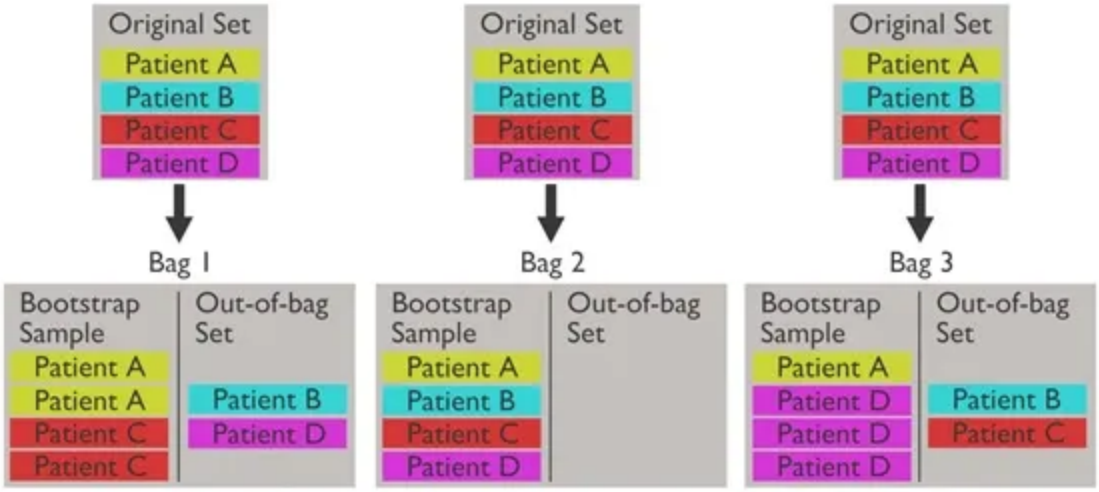
2. Algorithm

1. Generate Bootstrap Samples $B_1, B_2 \ldots\ldots B_b$
   - Create B_b by picking points from $x_1, x_2, x_3 \ldots\ldots x_n$ randomly n times
   - A particular x_i can appear in B_b many times
2. Generate estimators $f(B_b)$ using data B_b, where each split is computed as follows
   - Randomly select m dimensions of $x \in R^d$ newly chosen for each b
   - Make the best split restricted to that subset of dimension

Another advantage of Random Forest is that it does not require a holdout dataset and hence can effectively work on smaller datasets. Instead of Test Errors, we can calculate Out of Bag (OOB) Errors. The framework for this is shown below :

3. Out of Bag Error

- For each Bag $B_1, B_2 \ldots\ldots B_b$ find observations which are not in the bag
- For each observation, find trees where observation was not used
  - Run only for those trees and take aggregate
  - Check with original value to generate Out of Bag Error



Example of Out of Bag Set Creation

Jupyter Lab

Here we explore data from LendingClub.com

Given many different factors including the FICO score of the borrower, the interest rate, and even the purpose of the loan, we attempt to make predictions on whether a particular loan would be paid back in full.

Why Decision Trees / Random Forests?

Decision trees are a great 'rough and ready' ML technique that can be applied to many different scenarios. They are intuitive, and fast, and they can deal with both numerical and categorical data. The biggest drawback of Decision Trees is their tendency to overfit the given data, resulting in errors in either variance or bias. Random forests combat this problem by employing many different Decision Trees on random samples of the data, and so are usually a more sensible choice when choosing an ML model.

Imports

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

Exploratory Analysis

```
loans = pd.read_csv('loan_data.csv')
```

```
loans.head()
```

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

The ‘not.fully.paid’ column is the one we are interested in predicting.

```
loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   credit.policy      9578 non-null   int64
 1   purpose            9578 non-null   object
 2   int.rate           9578 non-null   float64
 3   installment        9578 non-null   float64
 4   log.annual.inc     9578 non-null   float64
 5   dti                9578 non-null   float64
 6   fico               9578 non-null   int64
 7   days.with.cr.line  9578 non-null   float64
 8   revol.bal          9578 non-null   int64
 9   revol.util         9578 non-null   float64
 10  inq.last.6mths     9578 non-null   int64
 11  delinq.2yrs        9578 non-null   int64
```

```
 12  pub.rec             9578 non-null   int64
 13  not.fully.paid      9578 non-null   int64
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
```

```
loans.describe()
```

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9.578000e+03	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.767197	1.691396e+04	46.799236	1.577469	0.163708	0.062122	0.160054
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.930377	3.375619e+04	29.014417	2.200245	0.546215	0.262126	0.366676
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.958333	0.000000e+00	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820.000000	3.187000e+03	22.600000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.958333	8.596000e+03	46.300000	1.000000	0.000000	0.000000	0.000000
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730.000000	1.824950e+04	70.900000	2.000000	0.000000	0.000000	0.000000
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.958330	1.207359e+06	119.000000	33.000000	13.000000	5.000000	1.000000

Some columns Information

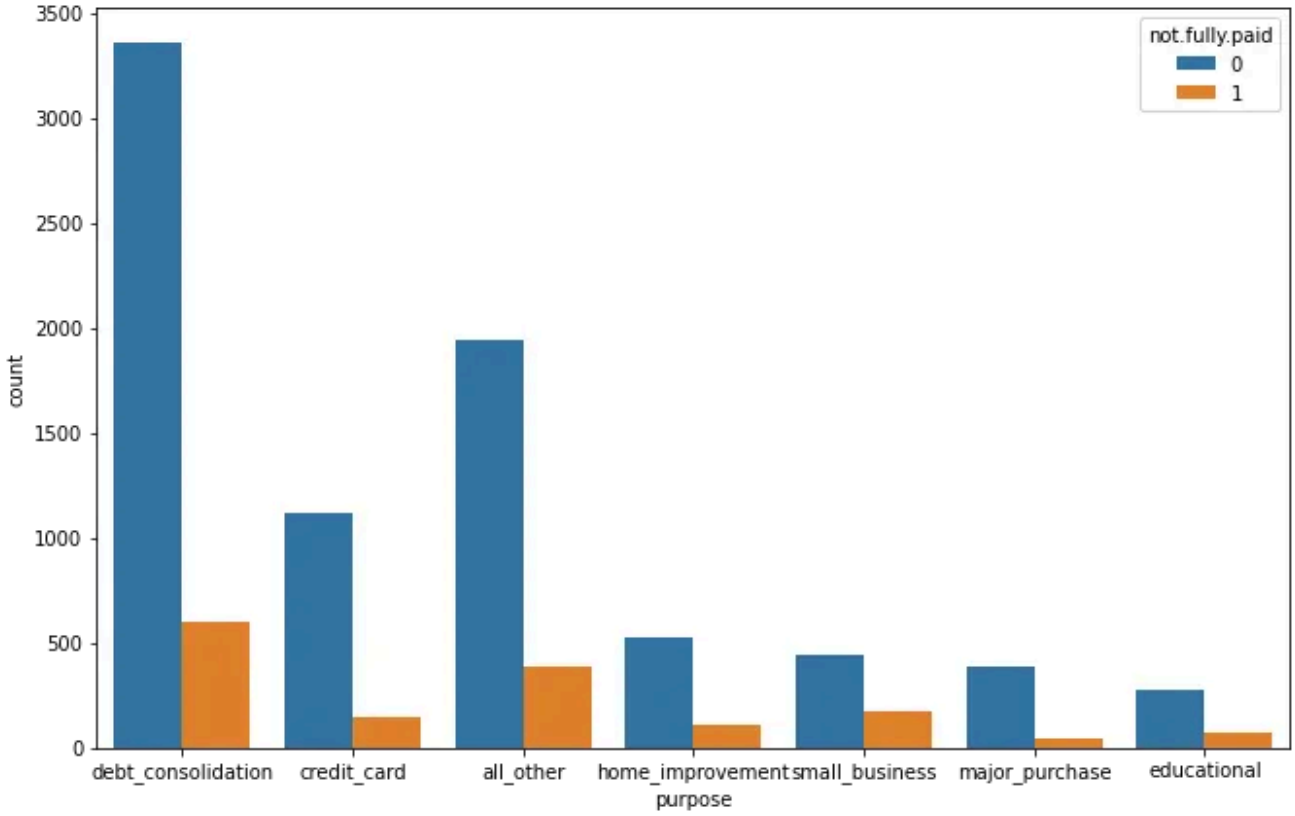
- credit.policy: 1 if the customer meets the credit underwriting criteria of LendingClub.com, and 0 otherwise.
- purpose: The purpose of the loan (takes values “credit_card”, “debt_consolidation”, “educational”, “major_purchase”, “small_business”, and “all_other”).
- int.rate: The interest rate of the loan, as a proportion (a rate of 11% would be stored as 0.11). Borrowers judged by LendingClub.com to be riskier are assigned higher interest rates.
- installment: The monthly installments owed by the borrower if the loan is funded.
- log.annual.inc: The natural log of the self-reported annual income of the borrower.
- dti: The debt-to-income ratio of the borrower (amount of debt divided by annual income).
- fico: The FICO credit score of the borrower.
- days.with.cr.line: The number of days the borrower has had a credit line.

- revol.bal: The borrower's revolving balance (amount unpaid at the end of the credit card billing cycle).
- revol.util: The borrower's revolving line utilization rate (the amount of the credit line used relative to total credit available).
- inq.last.6mths: The borrower's number of inquiries by creditors in the last 6 months.
- delinq.2yrs: The number of times the borrower had been 30+ days past due on a payment in the past 2 years.
- pub.rec: The borrower's number of derogatory public records (bankruptcy filings, tax liens, or judgments).

Data visualization

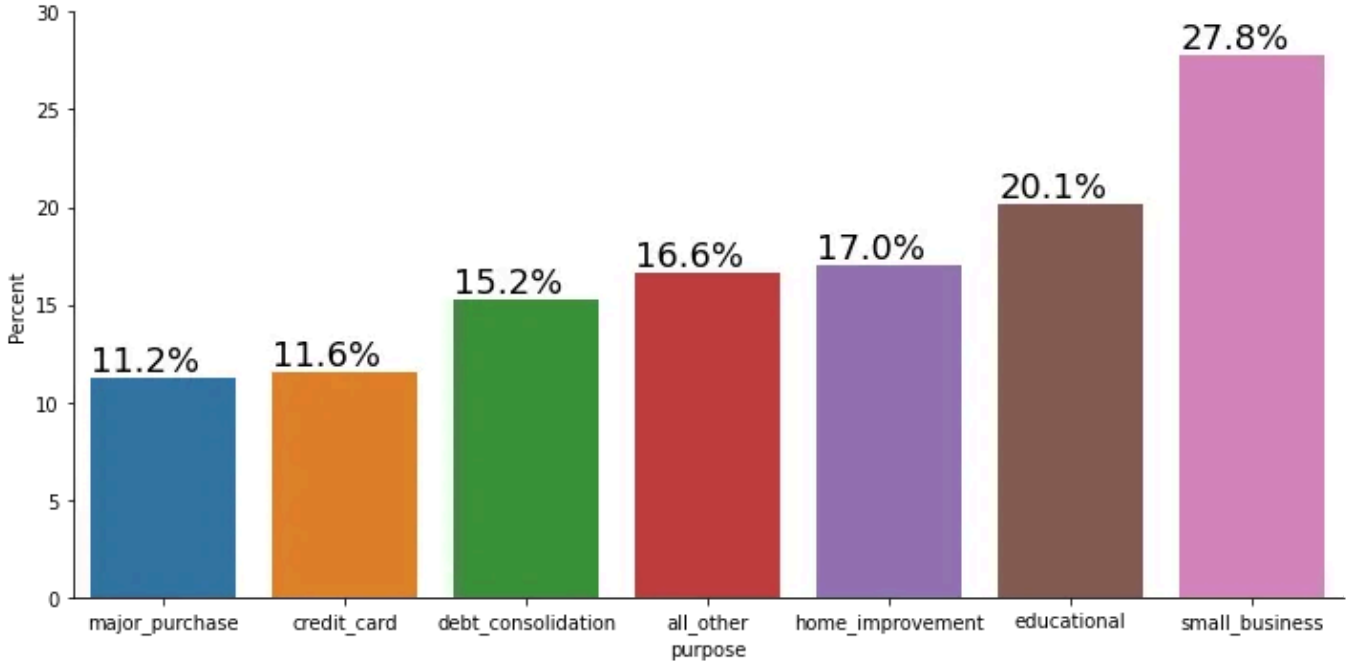
```
plt.figure(figsize=(11,7))
sns.countplot(loans['purpose'], hue = loans['not.fully.paid'])
```

```
We split our target function with respect to the purpose for which a
loan was taken.
```



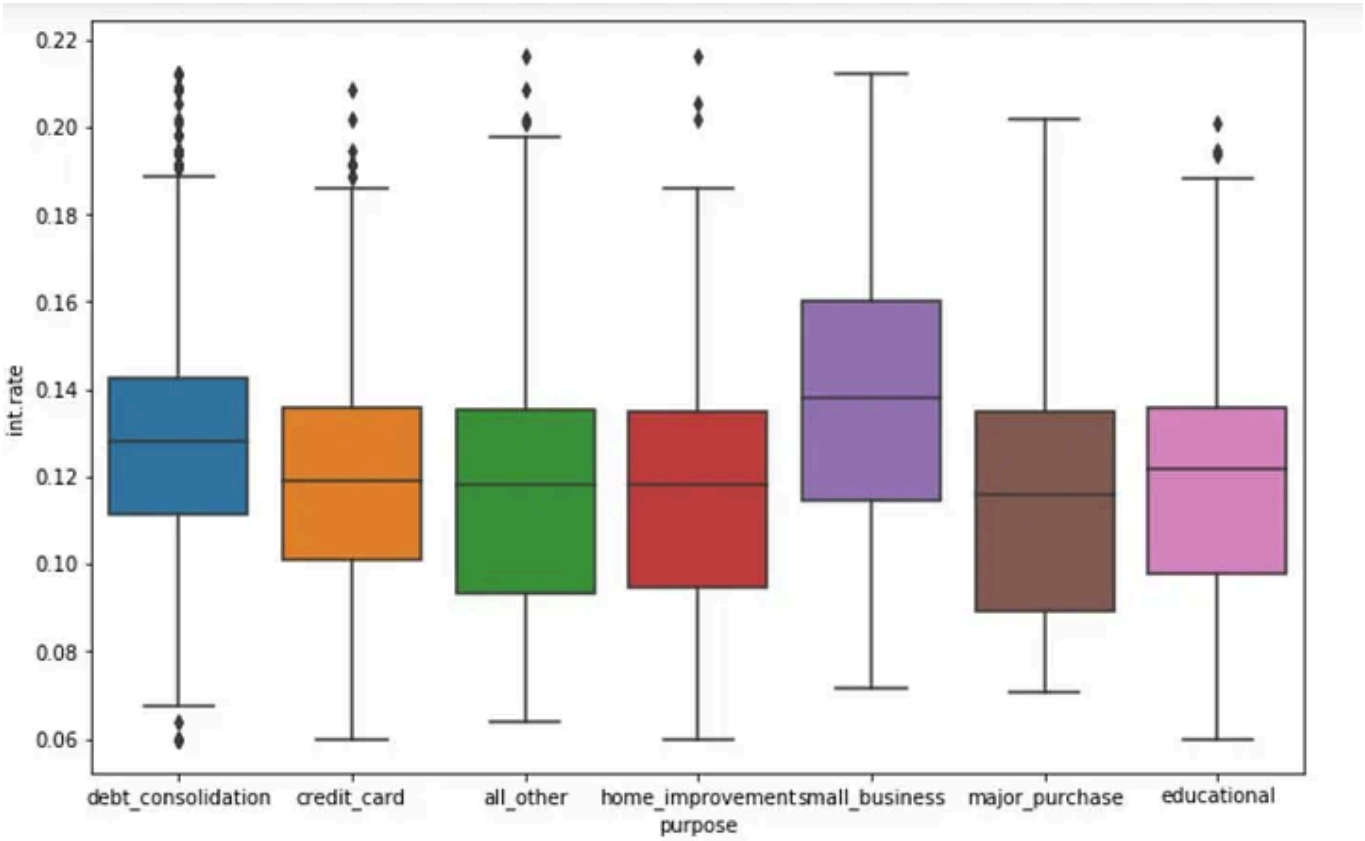

```
new_df = loans.groupby('purpose')
['not.fully.paid'].value_counts(normalize=True)
new_df = new_df.mul(100).rename('Percent').reset_index()

new_df1 = new_df[new_df["not.fully.paid"]==1]

new_df1=new_df1.sort_values("Percent")

g=sns.catplot(x="purpose", y='Percent', kind='bar', data=new_df1,
aspect=2)
g.ax.set_ylim(0,30)


for p in g.ax.patches:
    txt = str(p.get_height().round(1)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()

g.ax.text(txt_x,txt_y,txt,fontsize=18,verticalalignment='bottom',mult
ialignment='right')
```

We would like to understand the risk as a percentage hence we look at proportion of unpaid loans in each purpose type



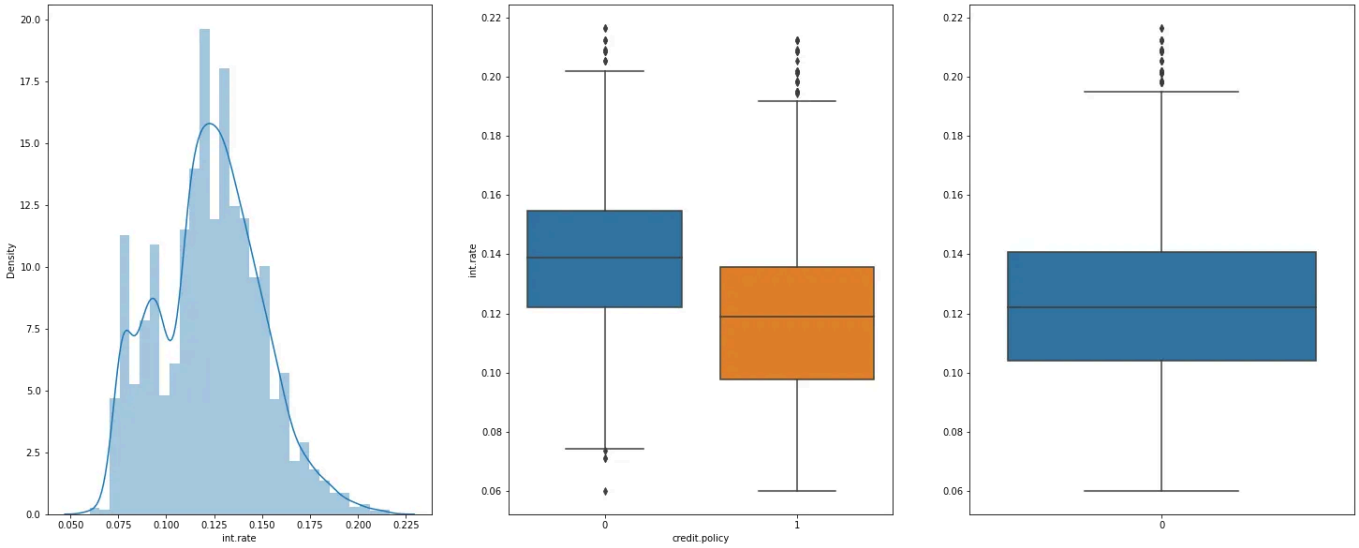

```
sns.boxplot(data =loans, x ='purpose', y=
loans['int.rate']).legend().set_visible(False)
```

Given the knowledge of risk basis purpose, we would like to understand if the APR offered to a customer take into account purpose.




```
df=loans
f,(ax1,ax2,ax3)= plt.subplots(1,3,figsize=(25,10))
sns.distplot(df['int.rate'], bins= 30,ax=ax1)
sns.boxplot(data =df, x ='credit.policy', y=
df['int.rate'],ax=ax2).legend().set_visible(False)
sns.boxplot(data = df['int.rate'], ax=ax3)
print("Interest Rate Distribution, Credit Policy range based on the
Credit policy , General Interest rate")
```

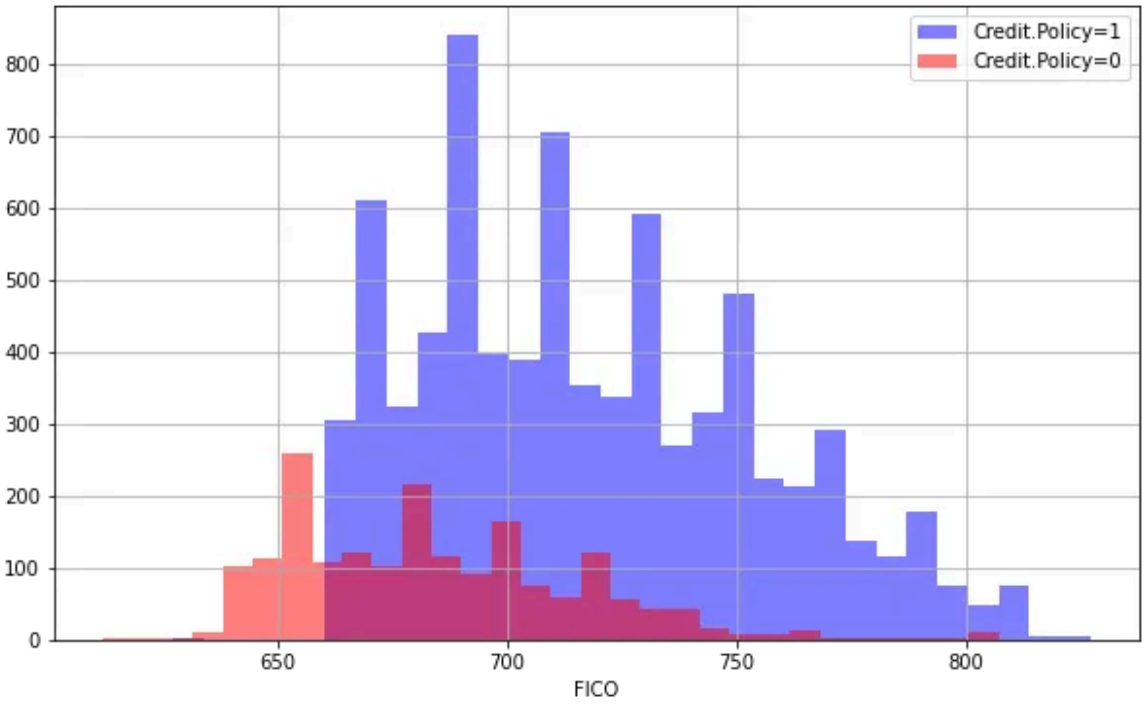
```
Interest Rate Distribution, Credit Policy range based on the Credit
policy , General Interest rate
```




```
plt.figure(figsize=(10,6))
loans[loans['credit.policy']==1]['fico'].hist(alpha=0.5,color='blue',

bins=30,label='Credit.Policy=1')
loans[loans['credit.policy']==0]['fico'].hist(alpha=0.5,color='red',

bins=30,label='Credit.Policy=0')
plt.legend()
plt.xlabel('FICO')
```

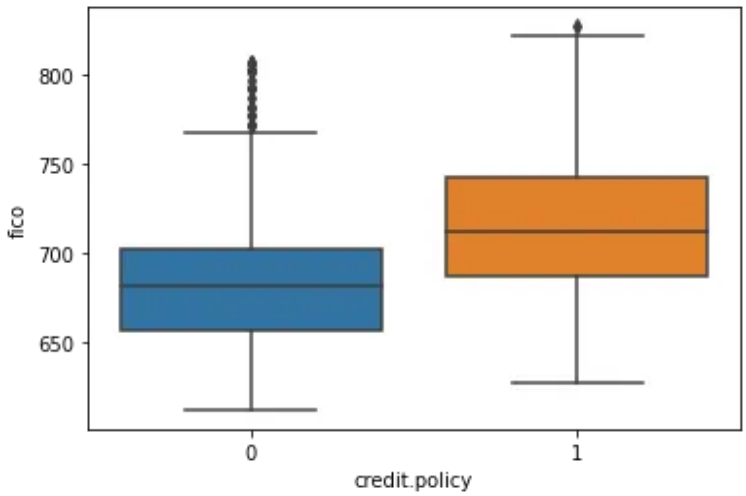
```
Text(0.5, 0, 'FICO')
```

To understand if Credit Policy Underwriting from Lending Club have FICO based cut-off for applying customers, we look at the following histogram.




```
sns.boxplot(data =loans, x ='credit.policy', y=
loans['fico']).legend().set_visible(False)
```

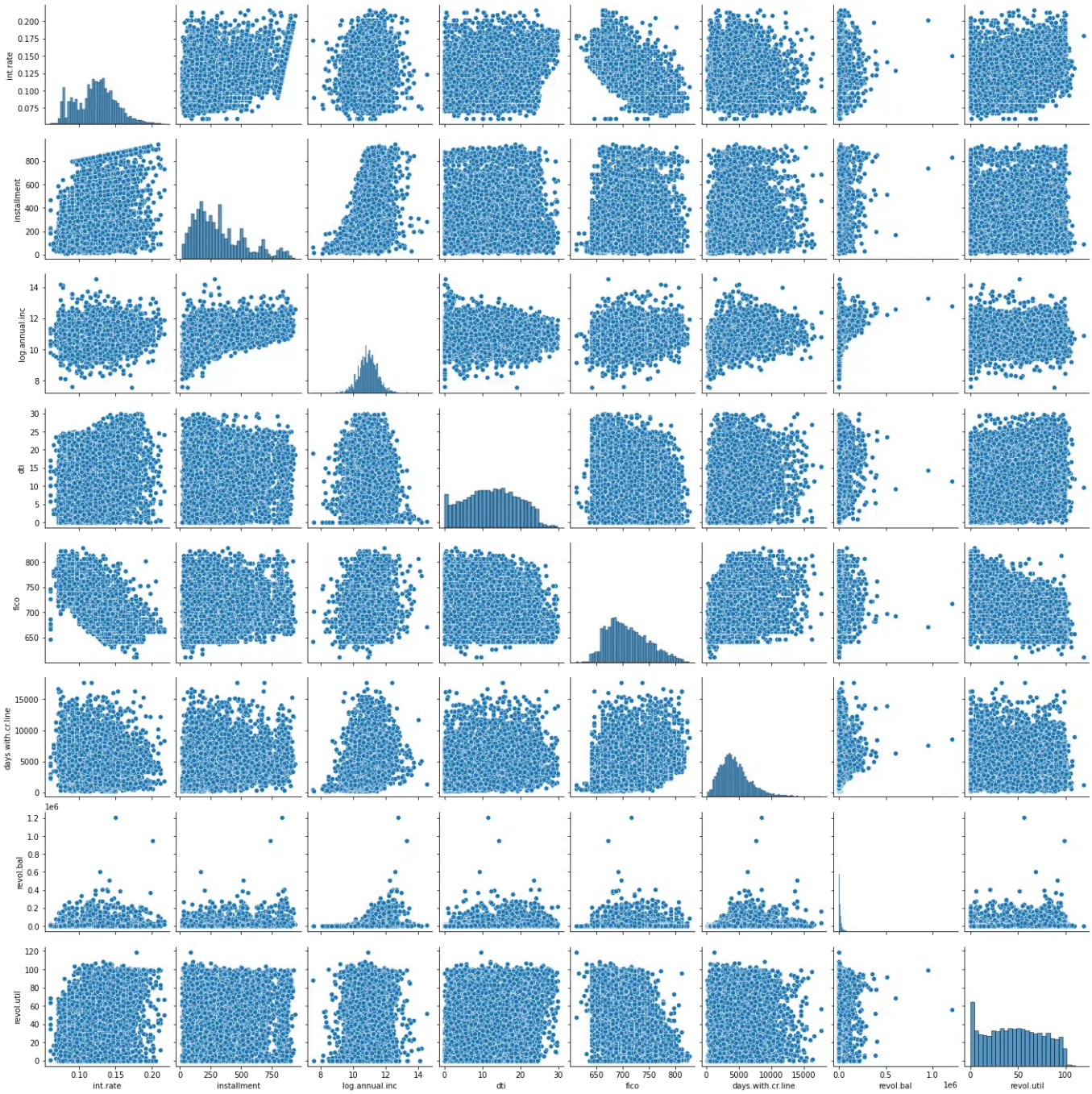
Credit Policy promotes individuals with Higher FICO



Let’s plot a seaborn pairplot between the numerical data:

```
sns.pairplot(loans.drop(['credit.policy', 'purpose',
       'inq.last.6mths', 'delinq.2yrs', 'pub.rec', 'not.fully.paid'],
axis=1))
```

```
<seaborn.axisgrid.PairGrid at 0x1d9e00432c8>
```



Cleaning

Let's transform the 'purpose' column to dummy variables so that we can include them in our analysis:

```
final_data = pd.get_dummies(loans,columns = ['purpose'],
drop_first=True)

final_data.head()
```

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid	purpose_credit_card	purpose_debt_consolidation	purpose_educational	purpose_home_improvement	purpose_major_purchase	purpose_small_business
0	1	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0	0	1	0	0	0	0
1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0	1	0	0	0	0	0
2	1	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0	0	1	0	0	0	0
3	1	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0	0	1	0	0	0	0
4	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0	1	0	0	0	0	0

```
from sklearn.model_selection import train_test_split

X= final_data.drop('not.fully.paid', axis=1)
y= final_data['not.fully.paid']
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size =
0.3, random_state = 101)
```

Decision Tree:

```
from sklearn.tree import DecisionTreeClassifier

dtree = DecisionTreeClassifier(class_weight=None, criterion='gini',
max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0,  random_state=None,
            splitter='best')

dtree.fit(X_train, y_train)

DecisionTreeClassifier()

pred = dtree.predict(X_test)
```

Evaluation

```
np.array((pred==y_test)).sum()
```

```
2104
```

```
from sklearn.metrics import classification_report, confusion_matrix
```

```
print(classification_report(y_test,pred))
```

```
precision    recall  f1-score   support

           0       0.86      0.82      0.84      2431
           1       0.19      0.23      0.21       443

    accuracy                           0.73      2874
   macro avg       0.52      0.53      0.53      2874
weighted avg       0.75      0.73      0.74      2874
```

```
print(confusion_matrix(y_test,pred))
```

```
[[2000  431]
 [ 339  104]]
```

Random Forest:

```
from sklearn.ensemble import RandomForestClassifier
```

```
dfor = RandomForestClassifier()
```

```
dfor.fit(X_train, y_train)
```

```
RandomForestClassifier()
```

```
pred2 = dfor.predict(X_test)
```

Evaluation

```
(y_test == pred2).sum()
```

```
2427
```

We can see that this has made a better prediction than a single tree

```
print(classification_report(y_test,pred2))

precision    recall  f1-score   support

           0       0.85      0.99      0.92      2431
           1       0.42      0.02      0.05       443

    accuracy                           0.84      2874
   macro avg       0.64      0.51      0.48      2874
weighted avg       0.78      0.84      0.78      2874

print(confusion_matrix(y_test,pred2))

[[2416   15]
 [ 432   11]]
```

Hyper Parameter Tuning ~ Random Forest

- n_estimators : Number of Trees in Random Forest
- max_features : Max Number of Features to be considered at each split
- max_depth : Max Depth of each estimator
- min_sample_split : Minimum Samples required for Valid Split
- min_samples_leaf : Minimum samples required at each leaf node

```
from sklearn.model_selection import RandomizedSearchCV
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000,
num = 10)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]
```

```
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               }
print(random_grid)
```

```
{'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800,
2000], 'max_features': ['auto', 'sqrt'], 'max_depth': [10, 20, 30,
40, 50, 60, 70, 80, 90, 100, 110, None], 'min_samples_split': [2, 5,
10], 'min_samples_leaf': [1, 2, 4]}
```

K-Fold Cross-Validation

The technique of cross-validation (CV) is best explained by example using the most common method, K-Fold CV. When we approach a machine learning problem, we make sure to split our data into a training and a testing set. In K-Fold CV, we further split our training set into K number of subsets, called folds. We then iteratively fit the model K times, each time training the data on K-1 of the folds and evaluating on the Kth fold (called the validation data).

```
# Use the random grid to search for best hyperparameters
# First create the base model to tune
rf = RandomForestClassifier()
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available
cores
rf_random = RandomizedSearchCV(estimator = rf, param_distributions =
random_grid, n_iter = 100, cv = 3, verbose=2, random_state=42, n_jobs
= -1)
# Fit the random search model
rf_random.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
```

```
RandomizedSearchCV(cv=3, estimator=RandomForestClassifier(),
```

```
n_iter=100, n_jobs=-1,
param_distributions={'max_depth': [10, 20, 30, 40, 50, 60,
                           70, 80, 90, 100, 110,None],
'max_features': ['auto', 'sqrt'],
'min_samples_leaf': [1, 2, 4],
'min_samples_split': [2, 5, 10],
'n_estimators': [200, 400, 600, 800,1000, 1200, 1400, 1600,
                                  1800, 2000]},      random_state=42,
verbose=2)

rf_random.best_params_

{'n_estimators': 200,
 'min_samples_split': 10,
 'min_samples_leaf': 2,
 'max_features': 'sqrt',
 'max_depth': 110}
```

References

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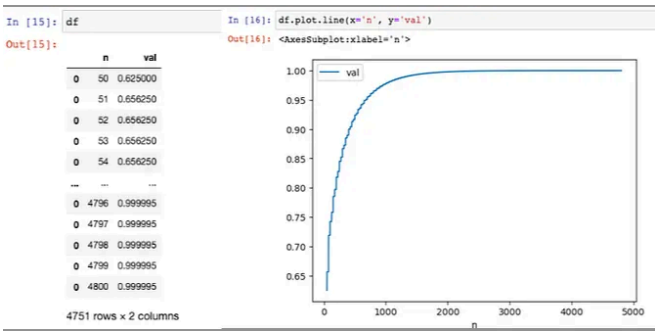

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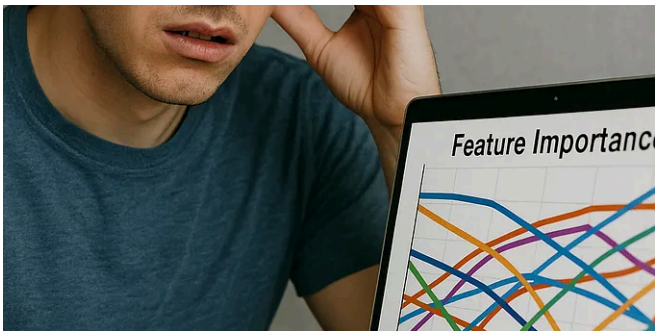

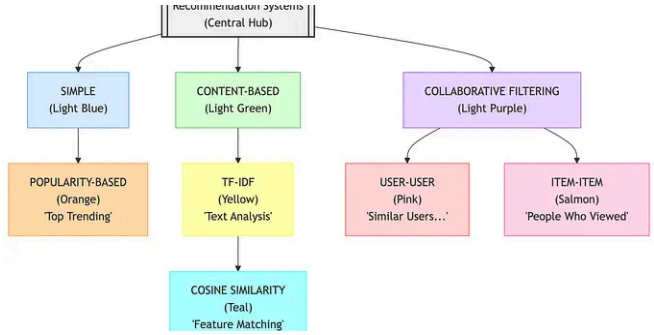

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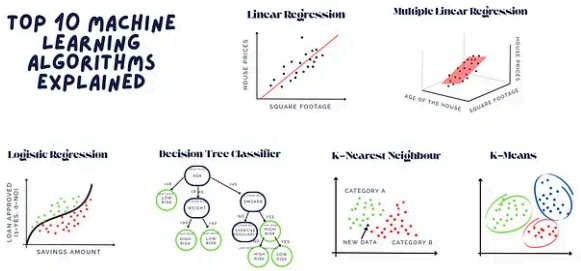

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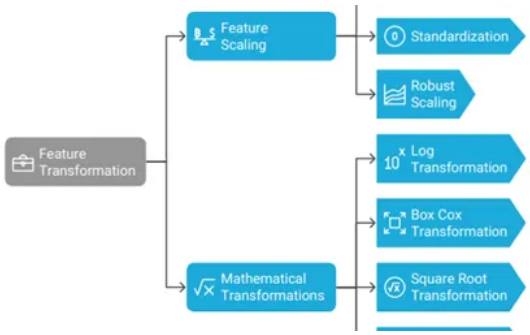

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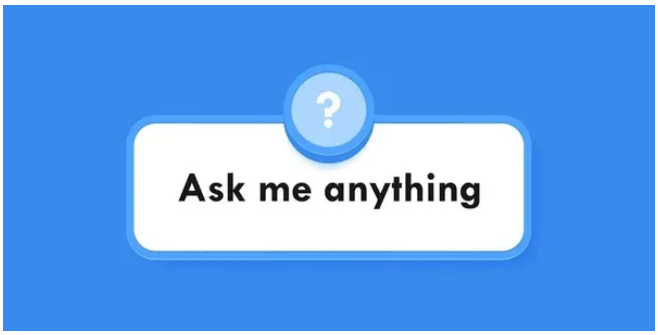

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