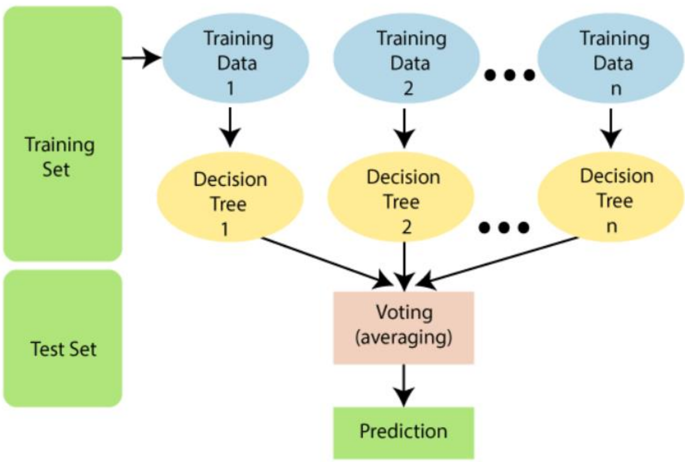
Random Forest Algorithm

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

The below diagram explains the working of the Random Forest algorithm:



Assumptions for Random Forest

Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random forest classifier:

- There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
- The predictions from each tree must have very low correlations.

Why use Random Forest?

Below are some points that explain why we should use the Random Forest algorithm:

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- It takes less training time as compared to other algorithms.
- It predicts output with high accuracy, even for the large dataset it runs efficiently.
- It can also maintain accuracy when a large proportion of data is missing.

How does Random Forest algorithm work?

Random Forest works in two-phase first is to create the random forest by combining N decision tree, and second is to make predictions for each tree created in the first phase.

The Working process can be explained in the below steps and diagram:

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

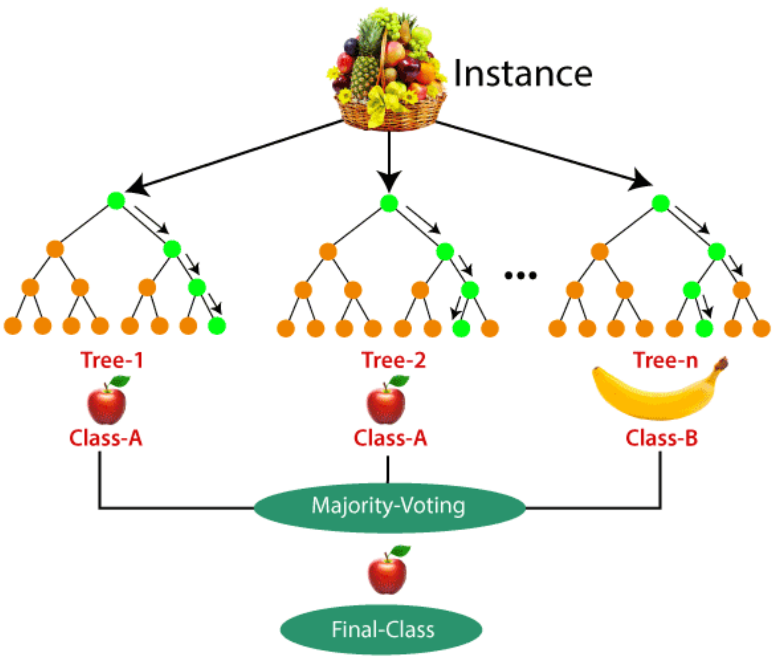
Step-3: Choose the number N for decision trees that you want to build.

Step-4: Repeat Step 1 & 2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

The working of the algorithm can be better understood by the below example:

Example: Suppose there is a dataset that contains multiple fruit images. So, this dataset is given to the Random forest classifier. The dataset is divided into subsets and given to each decision tree. During the training phase, each decision tree produces a prediction result, and when a new data point occurs, then based on the majority of results, the Random Forest classifier predicts the final decision. Consider the below image:



Applications of Random Forest

There are mainly four sectors where Random forest mostly used:

1. **Banking:** Banking sector mostly uses this algorithm for the identification of loan risk.
2. **Medicine:** With the help of this algorithm, disease trends and risks of the disease can be identified.
3. **Land Use:** We can identify the areas of similar land use by this algorithm.
4. **Marketing:** Marketing trends can be identified using this algorithm.

Advantages of Random Forest

- Random Forest is capable of performing both Classification and Regression tasks.
- It is capable of handling large datasets with high dimensionality.
- It enhances the accuracy of the model and prevents the overfitting issue.

Disadvantages of Random Forest

- Although random forest can be used for both classification and regression tasks, it is not more suitable for Regression tasks.

Python Implementation of Random Forest Algorithm

We will be exploring publicly available data from LendingClub.com. Lending Club connects people who need money (borrowers) with people who have money (investors). Hopefully, as an investor you would want to invest in people who showed a profile of having a high probability of paying you back. We will try to create a model that will help predict this.

Lending club had a very interesting year in 2016, so let's check out some of their data and keep the context in mind. This data is from before they even went public.

We will use lending data from 2007-2010 and be trying to classify and predict whether or not the borrower paid back their loan in full. You can download the data from here or just use the csv already provided. It's recommended you use the csv provided as it has been cleaned of NA values.

Here are what the columns represent:

- 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 more risky 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).

Import Libraries

Import the usual libraries for pandas and plotting. You can import sklearn later on**.**

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

** Check out the info(), head(), and describe() methods on loans.**

```
loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
credit.policy        9578 non-null int64
purpose              9578 non-null object
int.rate             9578 non-null float64
installment          9578 non-null float64
log.annual.inc       9578 non-null float64
dti                  9578 non-null float64
fico                 9578 non-null int64
days.with.cr.line    9578 non-null float64
revol.bal            9578 non-null int64
revol.util           9578 non-null float64
inq.last.6mths       9578 non-null int64
delinq.2yrs          9578 non-null int64
pub.rec              9578 non-null int64
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.2y
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9.578000e+03	9578.000000	9578.000000	9578.0000
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.767197	1.691396e+04	46.799236	1.577469	0.1637
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.930377	3.375619e+04	29.014417	2.200245	0.5462
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.958333	0.000000e+00	0.000000	0.000000	0.0000
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820.000000	3.187000e+03	22.600000	0.000000	0.0000
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.958333	8.596000e+03	46.300000	1.000000	0.0000
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730.000000	1.824950e+04	70.900000	2.000000	0.0000
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.958330	1.207359e+06	119.000000	33.000000	13.0000

```
loans.head()
```

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
1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

Exploratory Data Analysis

Let's do some data visualization! We'll use seaborn and pandas built-in plotting capabilities, but feel free to use whatever library you want. Don't worry about the colors matching, just worry about getting the main idea of the plot.

Create a histogram of two FICO distributions on top of each other, one for each credit.policy outcome.

```
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')
```

```
<matplotlib.text.Text at 0x119963f28>
```

Create a similar figure, except this time select by the not.fully.paid column.

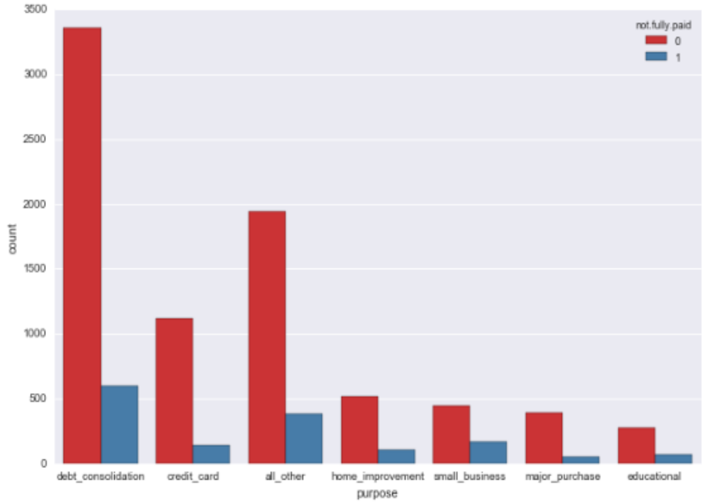
```
plt.figure(figsize=(10,6))
loans[loans['not.fully.paid']==1]['fico'].hist(alpha=0.5,color='blue',
                                               bins=30,label='not.fully.paid=1')
loans[loans['not.fully.paid']==0]['fico'].hist(alpha=0.5,color='red',
                                               bins=30,label='not.fully.paid=0')
plt.legend()
plt.xlabel('FICO')
```

```
<matplotlib.text.Text at 0x11c47a7f0>
```

Create a countplot using seaborn showing the counts of loans by purpose, with the color hue defined by not.fully.paid.

```
plt.figure(figsize=(11,7))
sns.countplot(x='purpose',hue='not.fully.paid',data=loans,palette='Set1')
```

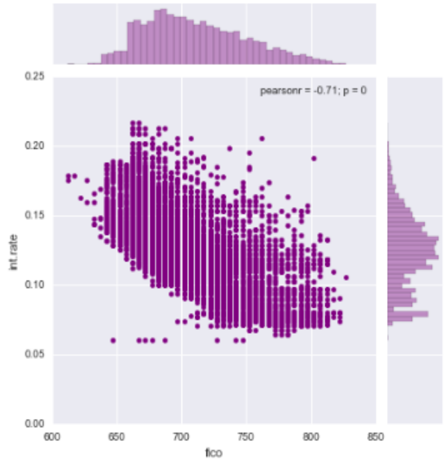
```
<matplotlib.axes._subplots.AxesSubplot at 0x119996828>
```



Let's see the trend between FICO score and interest rate. Recreate the following jointplot.

```
sns.jointplot(x='fico',y='int.rate',data=loans,color='purple')
```

```
<seaborn.axisgrid.JointGrid at 0x119963320>
```

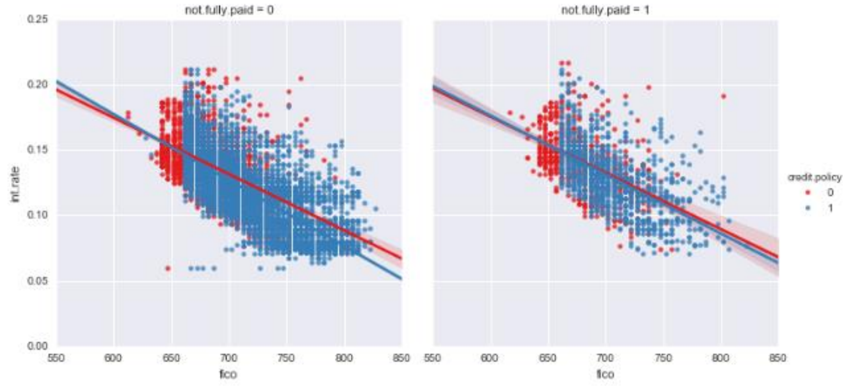


Create the following lmplots to see if the trend differed between not.fully.paid and credit.policy. Check the documentation for lmplot() if you can't figure out how to separate it into columns

```
plt.figure(figsize=(11,7))
sns.lmplot(y='int.rate',x='fico',data=loans,hue='credit.policy',
          col='not.fully.paid',palette='Set1')
```

```
<seaborn.axisgrid.FacetGrid at 0x11d34b668>

<matplotlib.figure.Figure at 0x11d3094e0>
```



Setting up the Data

Let's get ready to set up our data for our Random Forest Classification Model!

Check loans.info() again.

```
loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
credit.policy        9578 non-null int64
purpose              9578 non-null object
int.rate             9578 non-null float64
installment          9578 non-null float64
log.annual.inc       9578 non-null float64
dti                  9578 non-null float64
fico                 9578 non-null int64
days.with.cr.line    9578 non-null float64
revol.bal            9578 non-null int64
revol.util           9578 non-null float64
inq.last.6mths       9578 non-null int64
delinq.2yrs          9578 non-null int64
pub.rec              9578 non-null int64
not.fully.paid       9578 non-null int64
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
```

Categorical Features

Notice that the purpose column as categorical

That means we need to transform them using dummy variables so sklearn will be able to understand them. Let's do this in one clean step using pd.get_dummies.

Let's show you a way of dealing with these columns that can be expanded to multiple categorical features if necessary.Create a list of 1 element containing the string 'purpose'. Call this list cat_feats.

```
cat_feats = ['purpose']
```

Train Test Split

Now its time to split our data into a training set and a testing set!

Use sklearn to split your data into a training set and a testing set as we've done in the past.

```
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=0.30, random_state=101)
```

Training the Random Forest model

Now its time to train our model.Create an instance of the RandomForestClassifier class and fit it to our training data from the previous step.

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

```
rfc = RandomForestClassifier(n_estimators=600)
```

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

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=600, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

Predictions and Evaluation

Let's predict off the y_test values and evaluate our model.Predict the class of not.fully.paid for the X_test data.

```
predictions = rfc.predict(X_test)
```

Now create a classification report from the results.

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

```
print(classification_report(y_test,predictions))
```

```
             precision    recall  f1-score   support

          0       0.85      1.00      0.92      2431
          1       0.57      0.03      0.05       443

avg / total       0.81      0.85      0.78      2874
```

Show the Confusion Matrix for the predictions.

```
print(confusion_matrix(y_test,predictions))
```

```
[[2422    9]
 [ 431   12]]
```