



## Review of classification methods for fraud detection

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#### What is classification?

**Goal of classification:** Use known fraud cases to train a model to recognise new fraud cases

#### Examples:

- Email Spam/Not spam
- Transaction online fraudulent Yes/No
- Tumor Malignant/Benign?

Variable to predict:  $y \in 0, 1$ 

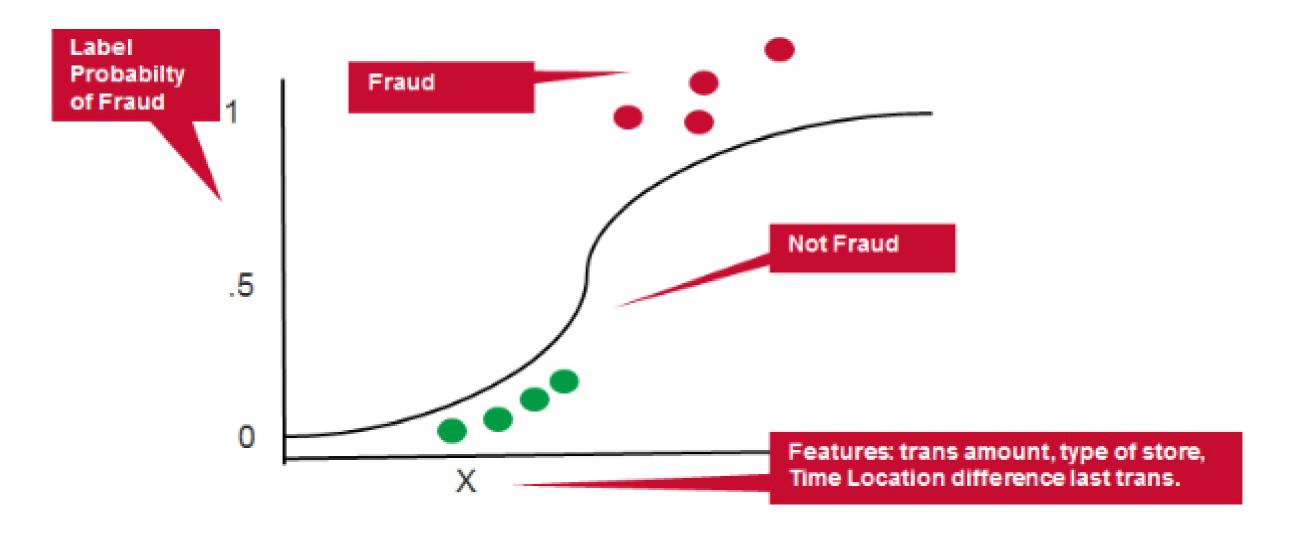
0: Negative class ("majority" normal cases)

1: Positive class ("minority" fraud cases)



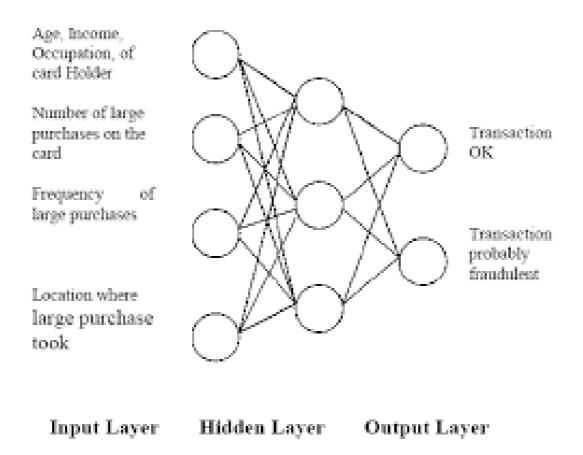
## Classification methods commonly used for fraud detection

• Logistic Regression



## Classification methods commonly used for fraud detection

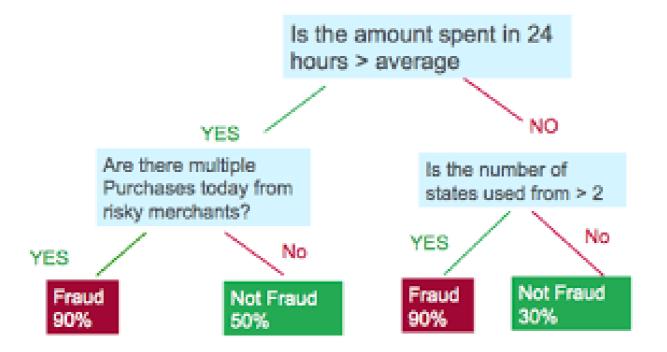
Neural Network





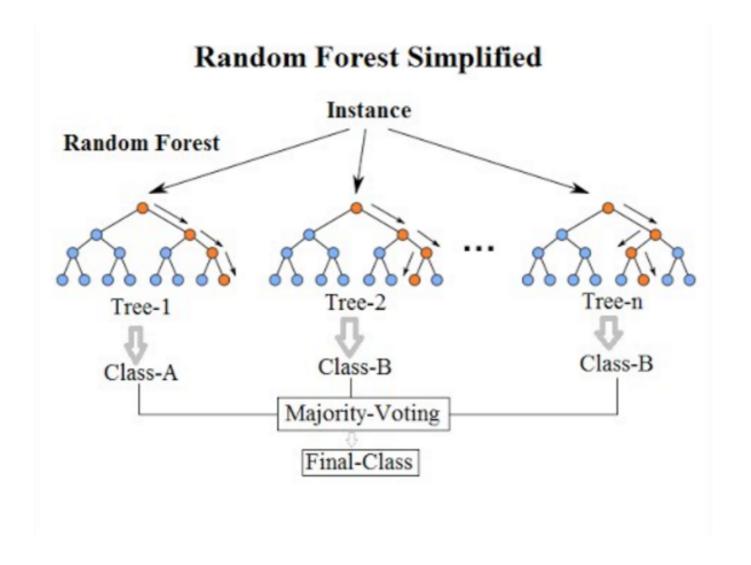
## Classification methods commonly used for fraud detection

- Decision trees
- Random Forests



#### **Decision Trees and Random Forests**

Random forests are a collection of trees on random subsets of features





#### Random Forests for fraud detection

```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(random_state=42)

model.fit(X_train, y_train)

predicted = model.predict(X_test)

print (metrics.accuracy_score(y_test, predicted))
0.991324200913242
```





## Let's practice!



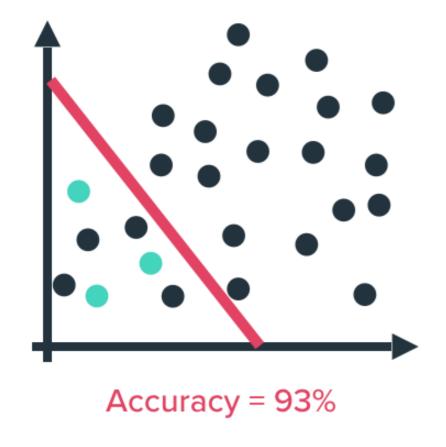


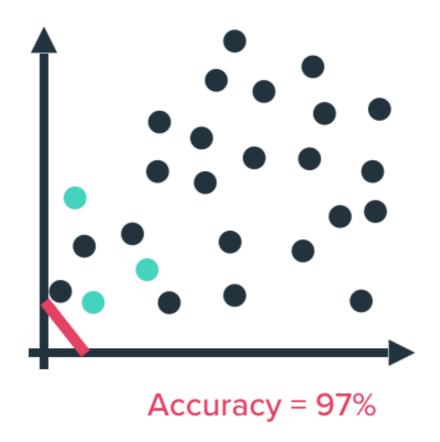
# Measuring fraud detection performance

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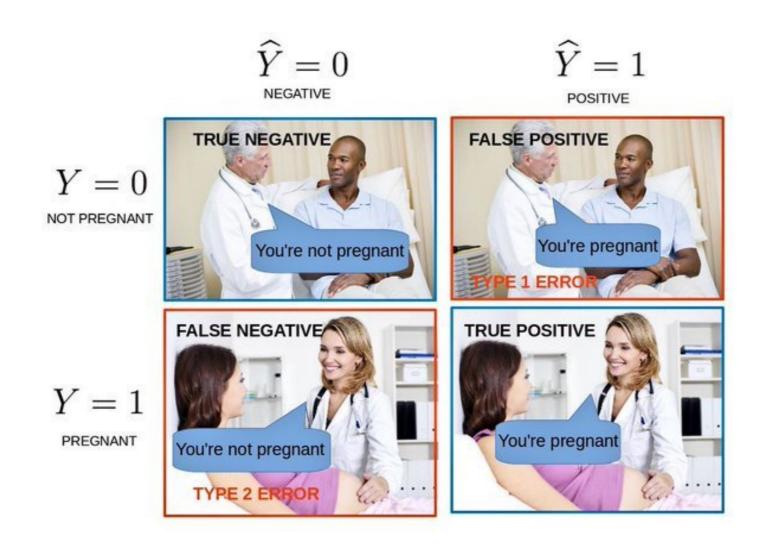
## Accuracy isn't everything

Throw accuracy out of the window when working on fraud detection problems

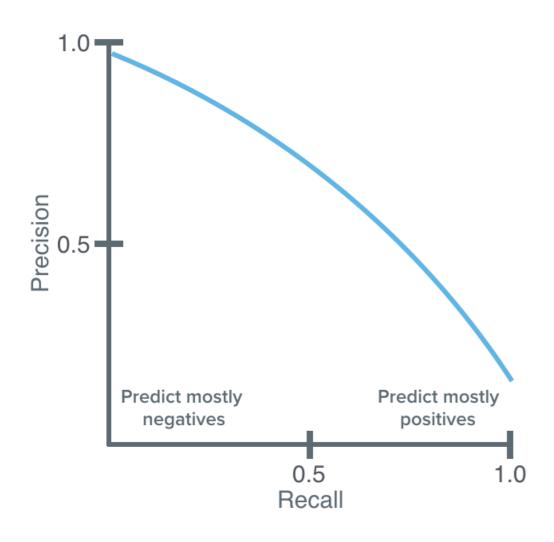




## False positives, false negatives and actual fraud caught



### Precision Recall trade-off



$$Precision = \frac{\#True\ Positives}{\#True\ Positives + \#False\ Positives}$$

$$Recall = \frac{\#True\ Positives}{\#True\ Positives + \#False\ Negatives}$$

$$F-measure = rac{2 imes Precision imes Recall}{Precision + Recall}$$
 
$$= rac{2 imes TP}{2 imes TP + FP + FN}$$



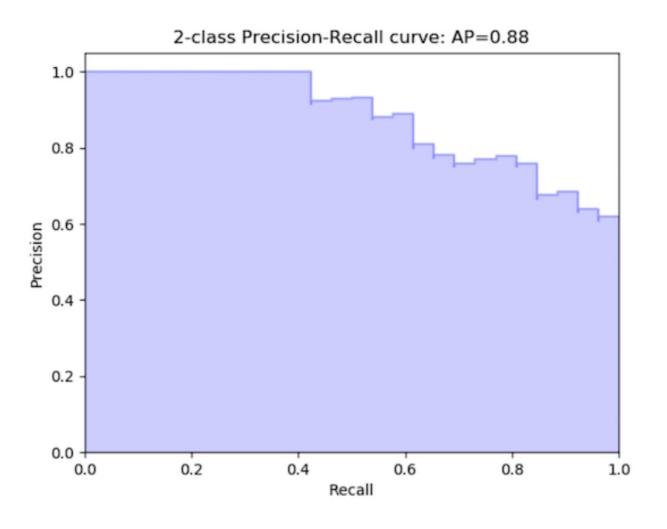
## Obtaining performance metrics

```
# Import the packages
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score

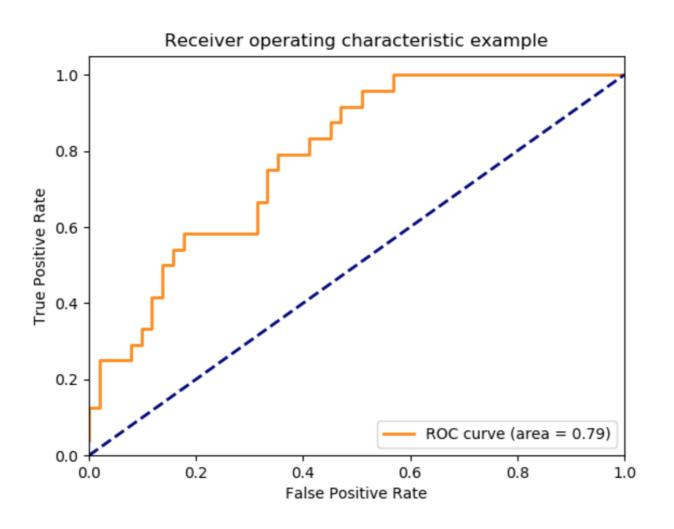
# Calculate average precision and the PR curve
average_precision = average_precision_score(y_test, predicted)

# Obtain precision and recall
precision, recall, _ = precision_recall_curve(y_test, predicted)
```

### Precision-Recall Curve



## ROC curve to compare algorithms



```
# Obtain model probabilities
probs = model.predict_proba(X_test)

# Print ROC_AUC score using probabilities
print(metrics.roc_auc_score(y_test, probs[:, 1]))
```



## Confusion matrix and classification report

```
from sklearn.metrics import classification report, confusion matrix
# Obtain predictions
predicted = model.predict(X test)
# Print classification report using predictions
print(classification report(y test, predicted))
 precision recall f1-score support
           0.99 1.00
       0.0
                              1.00
                                           2099
           0.96 0.80
                              0.87
      1.0
avg / total
           0.99 0.99
                              0.99
                                           2190
# Print confusion matrix using predictions
print(confusion matrix(y test, predicted))
[[2096
       31
  18
      73]]
```





## Let's practice!





## Adjusting your algorithms for fraud detection

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### Balanced weights

```
model = RandomForestClassifier(class_weight='balanced')

model = RandomForestClassifier(class_weight='balanced_subsample')

model = LogisticRegression(class_weight='balanced')

model = SVC(kernel='linear', class_weight='balanced', probability=True)
```



## Hyperparameter tuning for fraud detection

```
model = RandomForestClassifier(class_weight={0:1,1:4}, random_state=1)
model = LogisticRegression(class_weight={0:1,1:4}, random_state=1)

model = RandomForestClassifier(n_estimators=10,
criterion='gini'
```

```
model = RandomForestClassifier(n_estimators=10,
    criterion='gini',
    max_depth=None,
    min_samples_split=2,
    min_samples_leaf=1,
    max_features='auto',
    n_jobs=-1, class_weight=None)
```



## Using GridSearchCV

```
from sklearn.model_selection import GridSearchCV
# Create the parameter grid
param grid = {
    'max depth': [80, 90, 100, 110],
    'max features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min samples split': [8, 10, 12],
    'n estimators': [100, 200, 300, 1000]
# Define which model to use
model = RandomForestRegressor()
# Instantiate the grid search model
grid search model = GridSearchCV(estimator = model,
param grid = param grid, cv = 5,
n_{jobs} = -1, scoring='f1')
```



## Finding the best model with GridSearchCV

```
# Fit the grid search to the data
grid search model.fit(X train, y train)
# Get the optimal parameters
grid search model.best params
{ 'bootstrap': True,
 'max depth': 80,
 'max features': 3,
 'min samples leaf': 5,
 'min samples split': 12,
 'n estimators': 100}
# Get the best estimator results
grid search.best estimator
grid search.best score
```





## Let's practice!

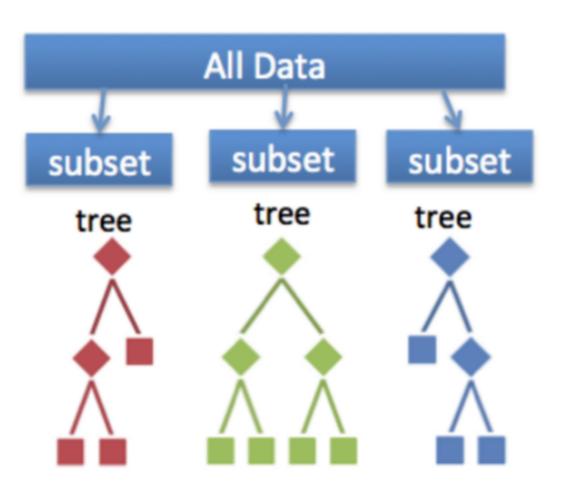




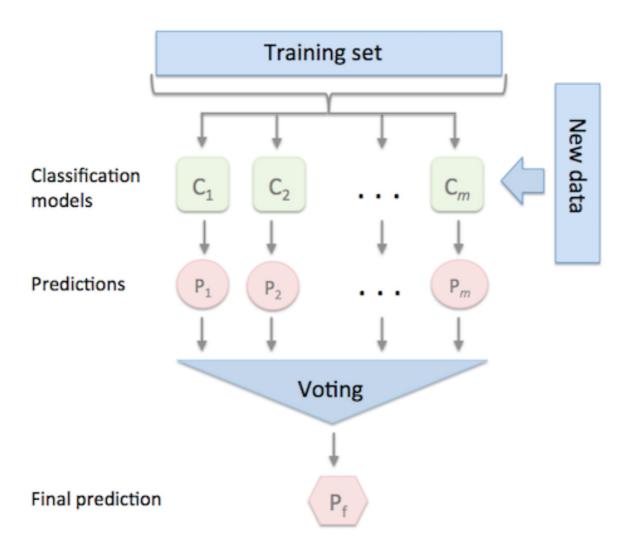
# Using ensemble methods to improve fraud detection

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## What are Ensemble Methods: Bagging versus Stacking



## Stacking Ensemble Methods





## Why use ensemble methods for fraud detection

#### Ensemble methods:

- Are robust
- Can help you avoid overfitting
- Can typically improve prediction performance
- Are a winning formula at prestigious Kaggle competitions



## **Voting Classifier**

```
from sklearn.ensemble import VotingClassifier

clf1 = LogisticRegression(random_state=1)
  clf2 = RandomForestClassifier(random_state=1)
  clf3 = GaussianNB()

ensemble_model = VotingClassifier(estimators=[('lr', clf1),
  ('rf', clf2), ('gnb', clf3)], voting='hard')

ensemble_model.fit(X_train, y_train)
  ensemble_model.predict(X_test)

VotingClassifier(estimators=[('lr', clf1), ('rf', clf2),
  ('gnb', clf3)], voting='soft', weights=[2,1,1])
```



### Reliable labels for fraud detection







## Let's practice