

BATMAN

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CS 514 – APPLIED ARTIFICIAL INTELLIGENCE – PROJECT V

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### **Santander Customer Satisfaction**

#### **Which customers are happy customers?**

From frontline support teams to C-suites, customer satisfaction is a key measure of success. Unhappy customers don't stick around. What's more, unhappy customers rarely voice their dissatisfaction before leaving.

Santander Bank is asking Kagglers to help them identify dissatisfied customers early in their relationship. Doing so would allow Santander to take proactive steps to improve a customer's happiness before it's too late.

In this competition, you'll work with hundreds of anonymized features to predict if a customer is satisfied or dissatisfied with their banking experience.

#### **Model:**

I have chosen Random Forest Classifier as my model. The following is the simple Random Forest Classifier implemented initially.

```

clf = RandomForestClassifier(n_estimators=100, max_depth=17,
random_state=1)

scores = cross_validation.cross_val_score(clf, X_train, y_train,
scoring='roc_auc', cv=5)

print(scores.mean())

clf.fit(X_train, y_train)

y_pred = clf.predict_proba(X_test)

```

The reason for choosing Random Forest Classifier was that the evaluated estimator performance for the above simple implementation was 0.821360825487, which is a good one to start with.

I have enhanced the Random Forest Classifier model with `n_estimators=800`, `random_state=1301`, `n_jobs=-1`, `criterion='gini'`, `class_weight='balanced'`, `max_depth=10`. The parameter `class_weight` is important. Especially in our case where the variable to predict, TARGET, is very unbalanced (skewed) in our sample. It is better to set `class_weight = "balanced_subsample"`, to have a balanced TARGET for each tree. But if we want weaker trees, `class_weight="balanced"` must be enough.

```

rfc = RandomForestClassifier (n_estimators=800,
random_state=1301, n_jobs=-1, criterion='gini',
class_weight='balanced', max_depth=10)

```

Cross validating the scores on a number of different random splits of the data has said to be an effective selection method for good features. The following link was very useful and gives more detailed explanation on it .

<http://blog.datadive.net/selecting-good-features-part-iii-random-forests/>

```
for train_idx, test_idx in cross_validation.StratifiedKFold(y, n_folds=5,
shuffle=True, random_state=1301):

    X_train, X_test = X_sel[train_idx], X_sel[test_idx]

    Y_train, Y_test = y[train_idx], y[test_idx]

    r = rfc.fit(X_train, Y_train)

    auc = roc_auc_score(Y_test, rfc.predict_proba(X_test)[:,:1])

    for i in range(X_sel.shape[1]):

        X_t = X_test.copy()

        np.random.shuffle(X_t[:, i])

        shuff_auc = roc_auc_score(Y_test, rfc.predict_proba(X_t)[:,:1])

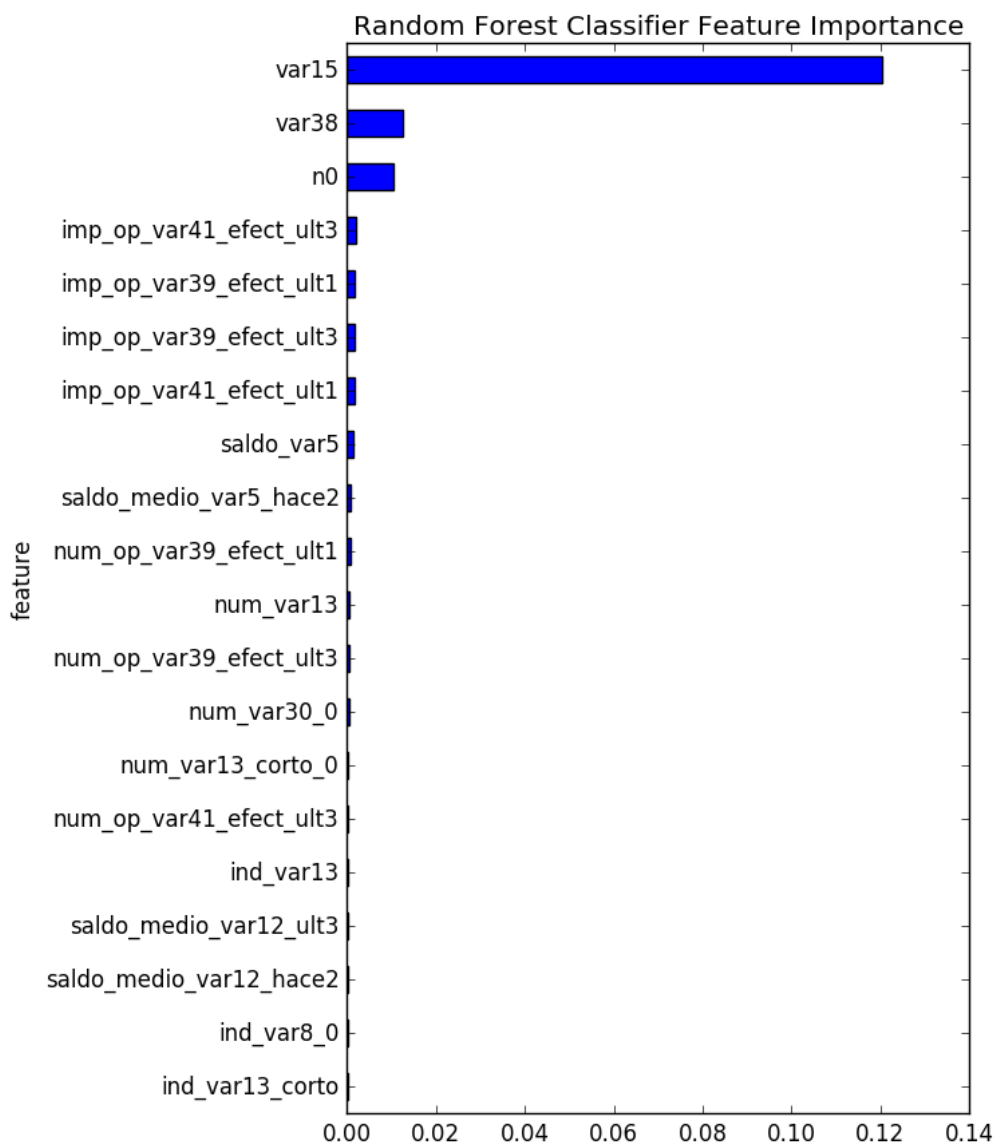
        scores[features[i]].append((auc-shuff_auc)/auc)

    print ("Features sorted by their score:")

print (sorted([(round(np.mean(score), 4), feat) for feat, score in scores.items()],
reverse=True))
```

Hence we can plot the Feature Importance chart from this information.

```
featp = ts.sort_values(by='score')[-20:].plot(kind='barh', x='feature', y='score',  
        legend=False, figsize=(6, 10))
```



**ROC (Receiver operating characteristic) Curve:**

The following snippet shows the plotting of ROC Curve.

```
plt.figure()

for name,clf in zip(names,clfs):

    clf.fit(X_train,y_train)

    y_proba = clf.predict_proba(X_test)[:,-1]

    print("Roc AUC:" + name, roc_auc_score(y_test,

clf.predict_proba(X_test)[:,-1],average='macro'))

fpr, tpr, thresholds = roc_curve(y_test, y_proba)

plt.plot(fpr, tpr, label=name)

plt.xlabel('False positive rate')

plt.ylabel('True positive rate')

plt.title('ROC curve')

plt.legend(loc='best')

plt.savefig('1.png')

plt.show()
```

