# COGS118A: An effort to replicate CMN06

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## Abstract

Taking Caruana and Niculescu-Mizil (2006) as a reference, this paper is my attempt in order to replicate a portion of its methods and results produced, using 4 different learning algorithms and 5 different data sets taken from UCI Machine Learning Repository over 3 different metrics. The algorithms consist of k-nearest neighbors, neural network, random forest and logistic regression.
**Keywords:** Logistic Regression, K-Nearest Neighbors, Random Forest, neural network

## 1. Introduction

Since Caruana and Niculescu-Mizil (2006), there has been a lot more comprehensive empirical studies comparing learning algorithms. However, replicability still plays an important role even for old papers. Hence, this project is my effort in order to present an analysis of old methods using new computational modules like Scikit-learn(Pedregosa et al. (2011)). The results of this project is mostly consistent with Caruana and Niculescu-Mizil (2006) with some slight negligible difference. Table 2 shows the performances over problems for each algorithm, where the Random Forest outperform on most dataset, with some insignificant difference with ANN if it was outperformed, followed by KNN and the worst of all is LOGREG. While in table 2, the random forest is the sole winner over 3 metrics, followed by ANN and KNN with some small but considered significant difference.

## 2. Methods

### 2.1 Learning algorithms

For the algorithms that I used, KNN from memory-based method, ANN from supervised neural networks, Random Forest from ensemble method and Logistic Regression from linear model method. I chose the hyper-parameters closely followed with those from CNM06 with minor changes.
**KNN**: I used 26 values of K ranging from 1 to 105 equally spaced. I only used KNN with Euclidean distance, with both uniform weighted and distance weighted.
**ANN**: I train neural nets with both stochastic gradient descent and adam backpropagation. The number of hidden units is varied 1,2,4,8,32,128. The number of batch size is 200, RELU is the main activation function and the maximum number of iterations is 500. The momentum of SGD is varied between 0, 0.2, 0.5 and 0.9

**Random Forest**: The forests have 1024 trees. The size of the feature set considered at each split is 1,2,4,6,8,10 and square root of the number of attributes.
**Logistic Regression (LOGREG)**: In order to encourage convergence in trade-off for speed, I set the maximum iterations to 5000. While training both unregularized and regularized models, I varied the regularization parameter from $10^{-8}$ to $10^4$.

### 2.2 Metrics

The metrics that I used for this paper are AUC-ROC, Accuracy and F1 score. Furthermore, metric Accuracy will be the base measure for comparisons between models and data sets. However, the metric alone might only captures a small picture of the whole, I have also include AUC-ROC and F1 for reference.

### 2.3 Data Sets

The five data sets used are ADULT, COV, LETTER.P2 like in Caruana and Niculescu-Mizil (2006) and AVILA, BEAN from the UCI Machine Learning Repository. Table 1 list the descriptions of the data sets. Just like in Caruana and Niculescu-Mizil (2006), COV data set from Blackard et al. (1998) has been converted to a binary problem by treating the largest class as the positive and the rest as negative, LETTER.p2 from Slate (1991) uses letters A-M as positives and the rest as negatives, yielding a well balanced problem. ADULT from Kohavi and Becker (1994) contains categorical features, hence I used one-hot-encoding in order to convert them to multiple binary features. AVILA data set from C. DeÂ Stefano (2018) has already been normalized by using the Z-normalization method so no processing is needed. Similar to COV data set, BEAN from Koklu and Ozkan (2020) has also been converted to a binary problem by treating the largest class as the positive and the rest as negative.

## 3. Experiment

### 3.1 Set-up

For each data set and algorithm combination, 5000 data samples are randomly sampled from 5 different times to fit into a 5-fold cross validation GridSearchCV in order to find the best hyper-parameters to optimize the corresponding score metrics. After having the best setting for each metrics, I used them to retrain the classifier into three different models, each optimize one metric. Afterwards, the models are used to make prediction on both training set and testing set, yielding both training and testing scores for 3 metrics. After which, the process is repeated for every classifier-dataset pair to get the desirable statistics for the tables below.

### 3.2 Results

Table 2 and 3 below are used to present the performance. The metrics score of the best-performing algorithm per data set are boldfaced while asterisks are used to denote algorithms that has near-similar performance with the best.

## 4. Conclusion

The best classifier for both data sets COV and AVILA is Random Forest while for ADULT and BEAN data sets, the ANN triumphs and KNN is the winner for LETTER data set. However, if we look closely, the datasets ADULT, LETTER and BEAN has achived performance that are not much significantly differs, except for LOGREG on LETTER. Over scoring metrics, RF uniformly outperforms the other classifiers, followed with ANN and KNN while LOGREG performing uniformly the worst of all.

If we were to compare Table 2 and Table 4, we can see that the performances of LOGREG on both training and testing set express no difference on all 3 metrics. This shows that LOGREG can be a bad choice to be chosen as a algorithm for binary classification problem compared to the other 3.

## Tables

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Table 1: Description of datasets

| Dataset | #Attr | Train size | Test size | %Poz |
|---|---|---|---|---|
| ADULT | 14/108 | 5000 | 25725 | 24.9% |
| COV | 54 | 5000 | 531012 | 48.76% |
| LETTER.P2 | 17 | 5000 | 15000 | 49.7% |
| AVILA | 11 | 5000 | 15867 | 41.08% |
| BEAN | 17 | 5000 | 8611 | 26.05% |

Table 2: Mean test set performance across trials over metrics

| Model | AUC | Accuracy | F1 |
|---|---|---|---|
| KNN | 0.843 | 0.865 | 0.809 |
| NN | 0.861* | 0.879* | 0.827 |
| RF | **0.890** | **0.907** | **0.862** |
| LOGREG | 0.770 | 0.794 | 0.725 |

Table 3: mean test set performance across trials over by data set

| Model | ADULT | COV | LETTER.P2 | AVILA | BEAN |
|---|---|---|---|---|---|
| KNN | 0.737 | 0.784 | **0.952** | 0.785 | 0.937* |
| NN | **0.765** | 0.799 | 0.947* | 0.825 | **0.943** |
| RF | 0.761* | **0.820** | 0.947* | **0.965** | 0.940* |
| LOGREG | 0.757* | 0.754 | 0.729 | 0.634 | 0.941* |

Table 4: Mean training set performance across trials over metrics

| Model | AUC | Accuracy | F1 |
|---|---|---|---|
| KNN | 0.961 | 0.982 | 0.960 |
| NN | 0.911 | 0.928 | 0.879 |
| RF | 1 | 1 | 1 |
| LOGREG | 0.771 | 0.796 | 0.730 |

Table 5: Mean training set performance across trials over problems

| Model | ADULT | COV | LETTER.P2 | AVILA | BEAN |
|---|---|---|---|---|---|
| KNN | 0.843 | 1.0 | 1.0 | 1.0 | 0.995 |
| NN | 0.781 | 0.918 | 1.0 | 0.881 | 0.950 |
| RF | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| LOGREG | 0.762 | 0.757 | 0.728 | 0.643 | 0.940 |

Table 6: Raw training performance (Ordered tuple by trials)

| Dataset | KNN | NN |
|---|---|---|
| ADULT | (0.838,0.847,1,1,0.858) | (0.860,0.859,0.857,0.854,0.856) |
| COV | (1.0,1.0,1.0,1.0,1.0) | (0.931,0.929,0.922,0.923,0.934) |
| LETTER.P2 | (1.0,1.0,1.0,1.0,1.0) | (1.0,1.0,1.0,1.0,0.999) |
| AVILA | (1.0,1.0,1.0,1.0,1.0) | (0.892,0.889,0.890,0.892,.889) |
| BEAN | (1.0,1.0,1.0,1.0,1.0) | (0.964,0.960,0.966,0.962,0.965) |

Table 7: Raw training performance (Ordered tuple by trials)

| Dataset | RF | LR |
|---|---|---|
| ADULT | (1.0,1.0,1.0,1.0,1.0) | (0.842,0.851,0.847,0.850,0.851) |
| COV | (1.0,1.0,1.0,1.0,1.0) | (0.745,0.763,0.753,0.757,0.767) |
| LETTER.P2 | (1.0,1.0,1.0,1.0,1.0) | (0.736,0.727,0.721,0.730,0.720) |
| AVILA | (1.0,1.0,1.0,1.0,1.0) | (0.688,0.688,0.694,0.699,0.689) |
| BEAN | (1.0,1.0,1.0,1.0,1.0) | (0.955,0.958,0.958,0.956,0.959) |

Table 8: Raw testing performance (Ordered tuple by trials)

| Dataset | KNN | NN |
|---|---|---|
| ADULT | (0.834,0.831,0.834,0.832,0.831) | (0.850,0.849,0.848,0.851,0.849) |
| COV | (0.782,0.783,0.787,0.783,0.780) | (0.801,0.803,0.804,0.798,0.804) |
| LETTER.P2 | (0.959,0.956,0.948,0.954,0.952) | (0.943,0.947,0.948,0.946,0.950) |
| AVILA | (0.803,0.804,0.803,0.801,0.788) | (0.836,0.838,0.841,0.838,0.831) |
| BEAN | (0.960,0.954,0.953,0.953,0.958) | (0.959,0.960,0.959,0.958,0.959) |

Table 9: Raw testing performance (Ordered tuple by trials)

| Dataset | RF | LR |
|---|---|---|
| ADULT | (0.842,0.850,0.846,0.847,0.846) | (0.846,0.846,0.846,0.843,0.847) |
| COV | (0.824,0.820,0.816,0.814,0.824) | (0.757,0.754,0.751,0.755,0.754) |
| LETTER.P2 | (0.947,0.945,0.948,0.946,0.950) | (0.730,0.730,0.721,0.726,0.734) |
| AVILA | (0.975,0.966,0.958,0.972,0.970) | (0.685,0.684,0.685,0.685,0.681) |
| BEAN | (0.955,0.958,0.957,0.956,0.956) | (0.957,0.956,0.957,0.956,0.957) |

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