

# Big Data Analytics Project : Dataset Adult from UCI

Mohammed Meftah, Raunaq Paul and Binxiang Xiang

16<sup>th</sup> January 2017

## Contents

<b>1</b>	<b>Introduction</b>	<b>2</b>
<b>2</b>	<b>Dataset description</b>	<b>2</b>
<b>3</b>	<b>Data processing</b>	<b>3</b>
3.1	Basic processing : . . . . .	3
3.2	Advanced processing : . . . . .	3
<b>4</b>	<b>Analysis</b>	<b>4</b>
<b>5</b>	<b>Methodology and results</b>	<b>4</b>
<b>6</b>	<b>Conclusion</b>	<b>4</b>

# 1 Introduction

For this project, we have decided to work on the dataset Adult from UCI. This is a classification dataset with two classes, as we have to understand and predict whether a person earns less or more than 50k dollars a year, according to the provided features. Section 2 describes in details the used dataset Adult. Section 3 highlights how we first processed data. Section 4 shows some statistical analysis on the dataset. Section 5 presents the methodology and the performances of different algorithms (list of tried algo to add) on the prediction of our target variable.

## 2 Dataset description

The raw dataset has 48842 rows and 15 columns including the target variable. This data is originally from the american census bureau and should be representative of the american population. This dataset is mixing continuous variables and discrete variables as follows :

**age** : continuous, age of the individual.

**fnlwgt** : continuous, the number of people the observation should represent, not useful for us.

**workclass** : discrete, 8 categories representing the type of the employer of the individual ( Private, Federal-gov, Never-worked ...).

**education** : discrete, 16 categories representing the highest level of education achieved by the individual (Bachelors, Masters, Doctorate, Highschool grad ... ).

**educationnum** : continuous, number of years of education.

**mstatus** : discrete, 7 categories representing the marital status of the individual (Divorced, Never-married, Separated ... ).

**occupation** : discrete, 14 categories representing the occupation of the individual (Tech-support, Sales, Exec-managerial, Other-service ...).

**relationship** : discrete, 6 categories representing the relationship of the individual, we don't know with who so this variable is not very clear (Wife, Husband, Own-child ...).

**race** : discrete, 5 categories representing the race of the individual (White, Asian-Pac-Islander, Black, Amer-Indian-Eskimo and Other).

**sex** : discrete, sex of the individual (Female or Male).

**capitalgain** : continuous, represents the recorded capital gains.

**capitalloss** : continuous, represents the recorded capital losses.

**hoursperweek** : continuous, represents the number of hours worked per week.

**nativecountry** : discrete, 41 categories representing the country of origin of the individual.

**target** : discrete, variable to predict, 2 classes ( $\leq 50k\$$  or  $> 50k\$$ ).

For the next sections, these names will be used to refer to the corresponding variable.

## 3 Data processing

In this section, we explain the different steps of processing we did on our raw dataset.

### 3.1 Basic processing :

We did perform some basic processing as a first step :

- Remove the variable *fnlwgt*, as it is not an information on the individual.
- Remove the variable *education*, as it contains the same information as the variable *educationnum* and we would prefer to work with a continuous variable.
- Transform the target variable into binary values, 0 if  $\leq 50k\$$  1 if  $> 50k\$$ .
- Remove rows with missing values, indeed variables *workclass*, *occupation* and *nativecountry* don't always have values. It represents 3620 rows.
- Scale continuous variables : *educationnum*, *capitalgain*, *capitalloss*, *hoursperweek*

After these steps, the new dataset has 45222 rows. And 24.8% of the observations are in the class 1 and 75.2% are in the class 0.

### 3.2 Advanced processing :

As the discrete variable *nativecountry* contains 41 categories where the main one (United States) represents 91.3% of the total, we have decided to group countries together into bigger categories. We don't change United-States, Canada, Japan, China, India , Iran and Mexico. The changes are the following :

New value	Old values concerned
WEurope	England, France, Germany, Holand-Netherlands, Ireland, Italy, Portugal, Scotland
EEurope	Greece, Hungary, South, Yugoslavia
SEAsia	Cambodia, Laos, Philippines, Thailand, Vietnam
LatAmerica	Columbia, Cuba, Dominican-Republic, Ecuador, El-Salvador, Guatemala, Haiti, Honduras, Jamaica, Nicaragua, Outlying-US(Guam-USVI-etc), Peru, Puerto-Rico, Trinidad&Tobago
China	HongKong, Taiwan

After the transformation, our *nativecountry* variable has now 11 different values against 41 before. Of course, we lost some information but it should not be so significant as we regroup countries from same area and with similar economic situation.

## 4 Analysis

After the processing part, we can start to look at data and make some analysis by variable and with by class.

## 5 Methodology and results

## 6 Conclusion