# Income Prediction from the Adult Dataset

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### Description of the problem

- Main objectives:
  - Full multivariate analysis
  - Build a classifier that discriminates people based on its income
    - Two categories: more and less than 50k dollars per year
- Very interesting dataset:
  - Very interpretable
  - Large number of both features and instances
  - Mixture of numerical and categorical variables
  - Great opportunity to apply all the techniques learnt in MVA!
- It seems reasonable that the income is quite related to those socioeconomical features
- Good models are expected!

#### **Available Data**

#### Numerical variables

Age, Fnlwgt, EducationNum, CapitalGain, CapitalLoss, WorkingHours

#### Categorical variables

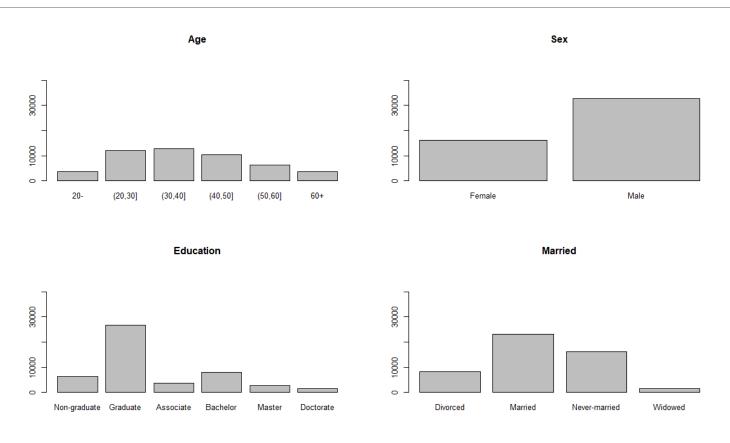
 Work, Education, MaritalStatus, Occupation, Relationship, Race, Sex, NativeCountry

- Some of the variables are uninformative or redundant
- Lots of modalities for the categorical variables
- 7.4% of instances have missing values!

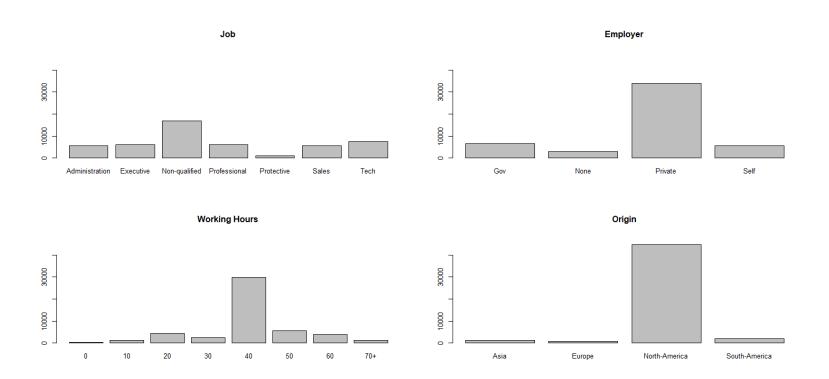
### Pre-process

- Redundant and uninformative variables removed
  - Fnlwgt, EducationNum, Relationship
- Numerical variables discretized
  - Age, WorkingHours, Capital (Gain + Loss)
- Categorical variables simplified
  - Work, Education, MaritalStatus, Occupation, Race, Sex, NativeCountry
- Some missing values have been explained
- The rest of missing values have been imputated

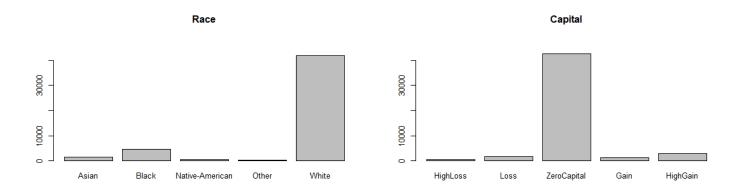
### Data summary



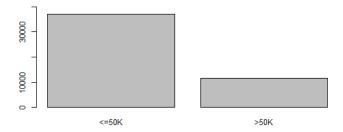
### Data summary



### Data summary





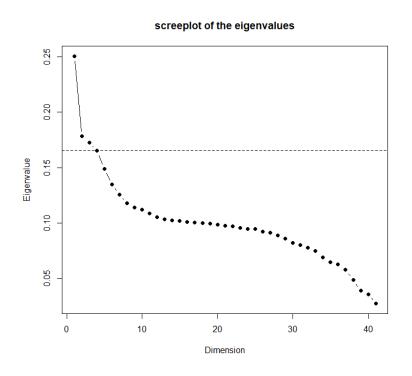


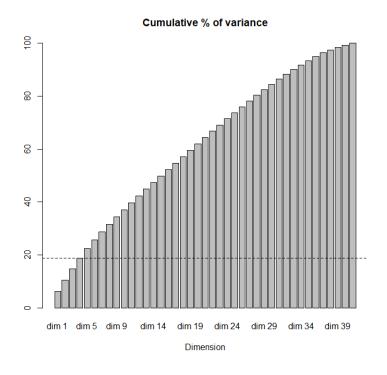
# Validation protocol

- Necessary in order to validate the results of the analysis
- High amount of data → train and test splits (50% each!)

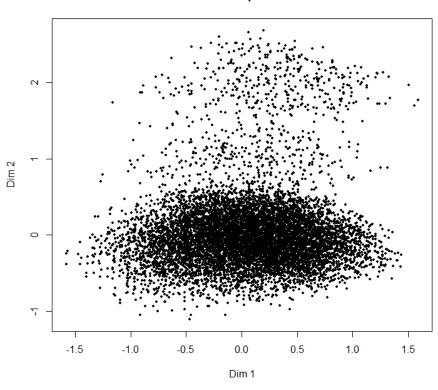
- Reduce data from 48,842 data samples to two sets of 24,421 data samples each
- Allows us to use some time-consuming techniques in the analysis

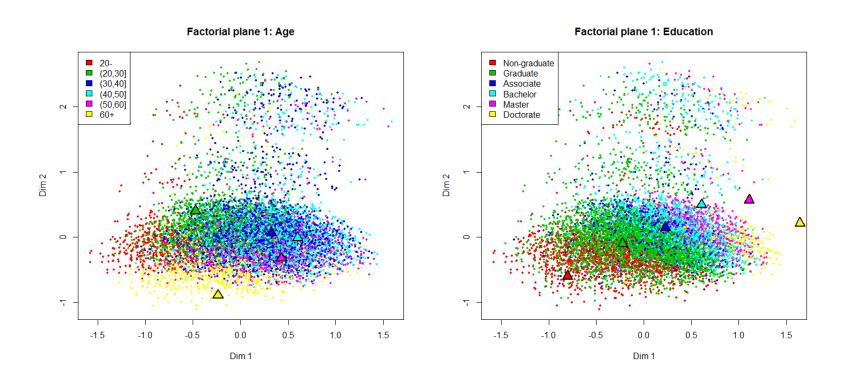
# Visualization (MCA)

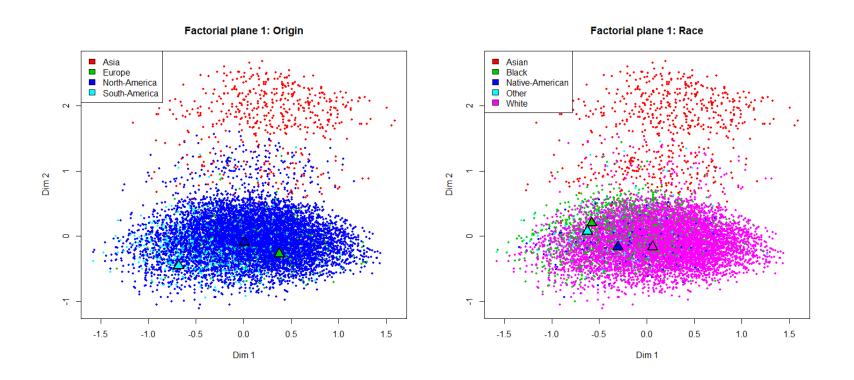


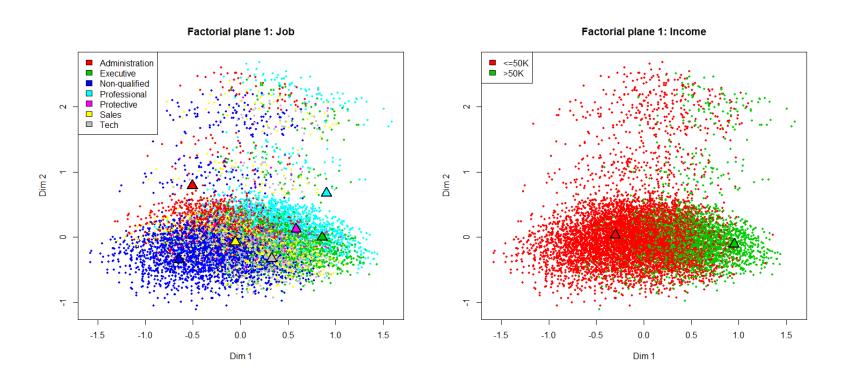


#### Factorial plane 1









### First component

- The First component is a latent variable that measures how successful a certain individual is
- Main modalities:
  - Age: between 30 and 60
  - Education: Bachelor or higher
  - Married: Married
  - Job: Executive, Professional or Protective
  - Working Hours: 40 or more
  - Income: More than 50K per year
- Better education and job is very correlated with Income!

#### Significant variables:

Variable	R2
Age	0.4227
Education	0.3191
Married	0.4004
Job	0.3939
WorkingHours	0.3404
Income	0.2860

### Second component

 The Second component is a latent variable that measures if a certain individual is Asian, whether being born there or being descendant of Asians

#### Main modalities:

Origin: Asia

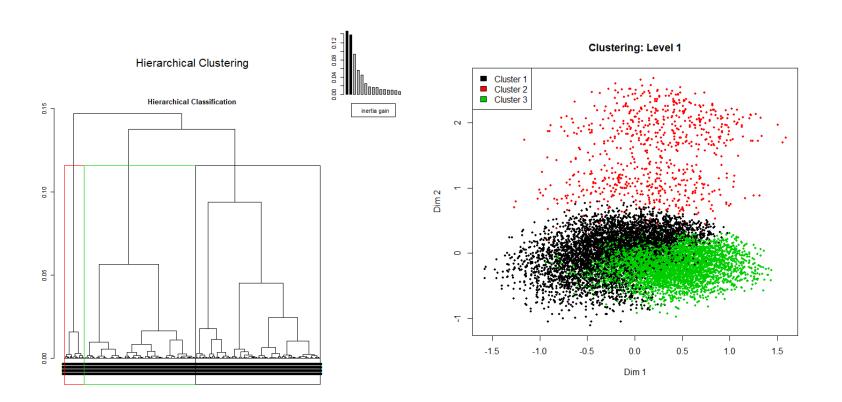
Race: Asian

 Cultural differences between Europeans, North-Americans and South-Americans is not as big as the difference with all of them and the Asian people

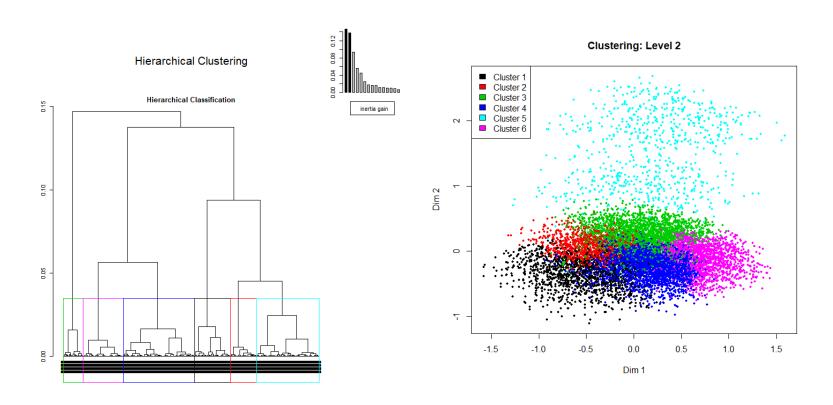
#### <u>Significant variables:</u>

Variable	R2
Origin	0.4782
Race	0.5022

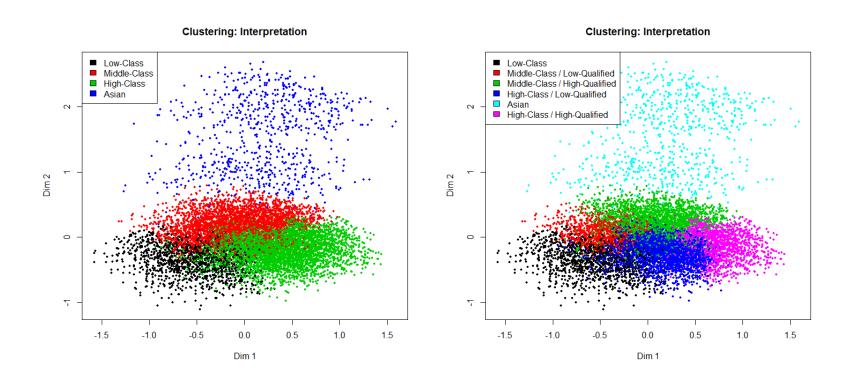
# Clustering



# Clustering



# Clustering Interpretation



### Sample validation

#### 1) Chi-squared test (individual tests)

Variable	P-value	Same?
Age	0.642	Yes
Sex	0.840	Yes
Education	0.124	Yes
Married	0.763	Yes
Job	0.328	Yes
Employer	0.136	Yes
Working Hours	0.880	Yes
Origin	0.144	Yes
Race	0.628	Yes
Capital	0.806	Yes
Income	0.656	Yes

**Individually,** all variables in both sets have the **same distribution** 

#### 2) Chi-squared test (single test)

In order to check homogeneity on the distribution of all the variables all together, we performed a Chisquared test over the combined contingency table of all the variables

P-value: 0.8668

**Globally,** we accept that both sets have the **same distribution** 

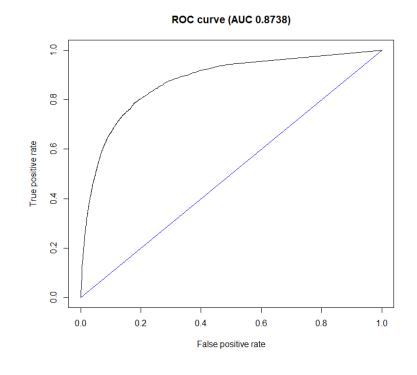
# Modelling: Random Forest

- Prediction model: Random Forest
  - Very robust
  - Handles categorical data
  - Proven successful in many challenging tasks
- A Random Forest is an ensemble of several Decision Trees
  - Greater predictive accuracy
  - Less prone to overfitting
- In this Project, an ensemble of 1000 trees is considered
- The rest of the parameters are optimized automatically

# Modelling: Results

Confusion Matrix		Predicted	
		<=50K	>50K
Actual	<=50K	17322	1277
	>50K	2404	3418

Metric	Value
Accuracy	0.8494
Precision	0.7280
Recall	0.5879
AUC	0.8738



#### Conclusions

- Very interesting information about people in the USA in 1994
- Lots of variables and modalities.
- Missing data is very interpretable
- Latent variables related to social status and origin culture
- Quite good model for Income classification
- In general, all the results were very interpretable
- Lots of MVA techniques have been applied

### Thank you!

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