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COMPAS Scores Defendant Recidivism

Machine Learning Model that pred

A Machine Learning Model that predicts if a defendant becomes a recidivist.

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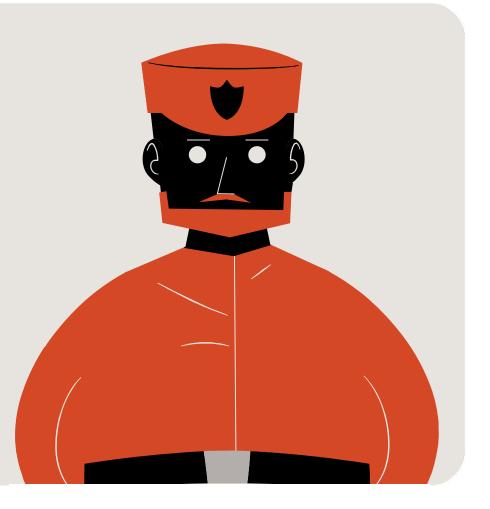


Table of contents



00

Introduction

A brief introduction to the project.

03

Data Preparation

Data Selection & Cleaning.

01

Business Understanding

Business Objectives & Data Mining Goals.

04

Modeling

Modeling Selection & Test Design.

02

Data Understanding

Data Description, Exploration & Quality.

05

Evaluation & Conclusion

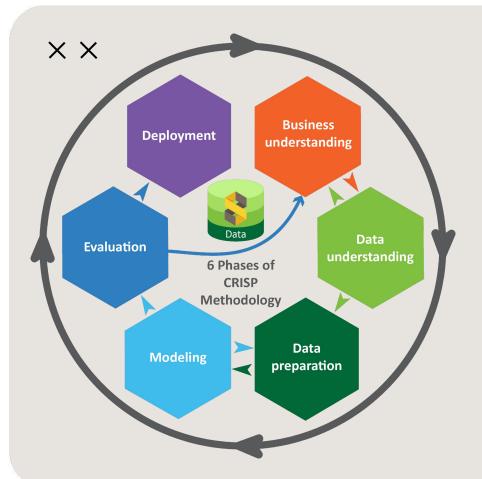
Results Evaluations & Process Review.



Introduction

Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) is a case management and decision support tool developed and owned by Northpointe used by U.S. courts to assess the likelihood of a defendant becoming a recidivist.





CRISP-DM Methodology

The CRoss Industry Standard Process for Data Mining is a process model that serves as the base for a data science process. It has six sequential phases.

Technologies, Tools and Libraries × ×



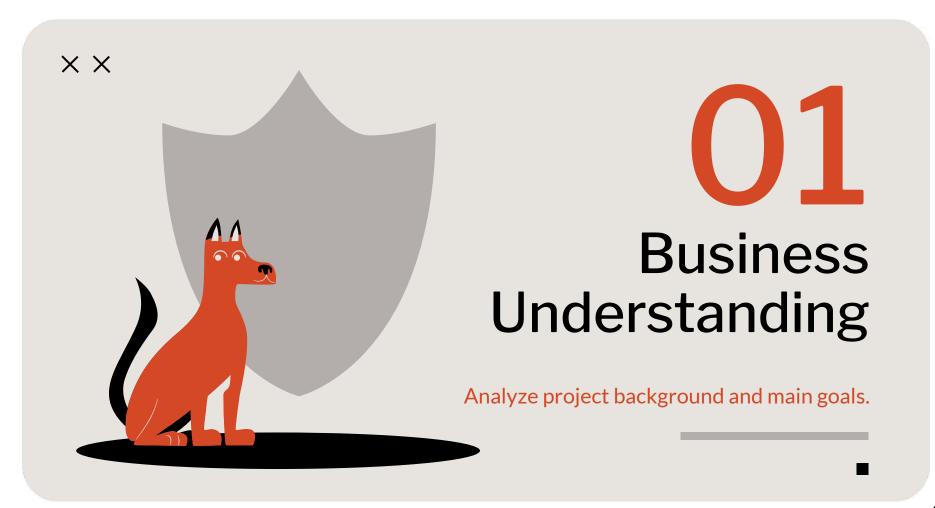














Background

The project is about **COMPAS Scores** dataset that collects over 11k records (registered from January 2013 to December 2014) and 47 attributes.

Each record represents a **criminal** with a name (first and last), date of birth, age, gender, ethnicity and other information about his/her arrest and screening date, type of offense and the recidivism.

Main Goals





- Determine and predict if a defendant becomes a recidivist.
- It will be useful for community corrections applications.



- Binary classification problem.
- If **is_recid** is equal to $0 \rightarrow$ the Criminal is not a recidivist.
- If is_recid is equal to 1 → the Criminal is a recidivist.

8

Other Goals

In addiction, we decided to more sub-goals to our analysis.



Violent Recid

Predict if a defendant becomes a violent recid or not.





Days before becoming recid

Predict in mean the number of days that pass from the first crime.





Days before becoming violent recid

Predict the number of days for a violent criminal.



Success Criteria





Success Criteria

Achieve a good level of accuracy, f-measure (≥0.90).



Business Success Criteria

- **Improve** the re-education plan for the defendants
- **Decrease** the cost to maintain detention institutions full
- **Invest** in readmission to improve the community wellness



Project Plan



Project Status

Project Step	Duration	Status	Start	End	Pred
01 Data Understanding	5 days	Completed -	10/05/2022	15/05/2022	//
02 Data Preparation	7 days	Completed -	16/05/2022	23/05/2022	01
03 Modeling	10 days	Completed •	24/05/2022	02/06/2022	02
04 Evaluation	5 days	Completed •	03/06/2022	08/06/2022	03
05 Deployment	4 days	In progress -	09/06/2022	12/06/2022	04

Gantt Diagram



02 **

Data Understanding

- → Data Description
- → Data Exploration
- → Data Quality



Data Description

The final dataset is composed of **11,757 instances** and **47 attributes** that we decided to analyze by dividing in three main groups:

Numerical Attributes

- id
- age
- juv_fel_count
- decile score
- juv_misd_count
- juv other count
- prisors count
- days_b_screening_arrest
- c_days_from_campas
- is_recid
- num_r_cases
- r_days_from_arrest
- is_violent_racid
- num_vr_cases
 - v_decile_score
- decile_score.1

Categorical Attributes

- name
- first
- last
- dob
- age_cat
- sex
- race
- compas_screening_date
- c_jail_in
- c_jail_out
- c_case_number
- c_offense_date
- c arrest date
- c charge degree
- c_charge_desc
- r case number

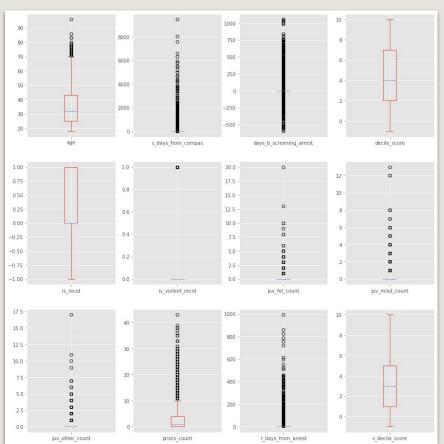
- r_charge_degree r offense date
- r_charge_desc
- r jail in
- r_jail_out
- vr_case_number
- vr_charge_degree
- vr_offense_date
- vr_charge_desc
- v_type_of_assessment
- v_score_text
- v_screening_date
 - type_of_assessment
- score_text
 - screening_date

Dates Attributes

- dob
- compas_screening_date
- c_jail_in
- c_jail_out
- c_offense_date
- c_arrest_date
- r_offense_date
- r_jail_in
- r_jail_out
- vr_offense_date
- v_screening_date
- screening date

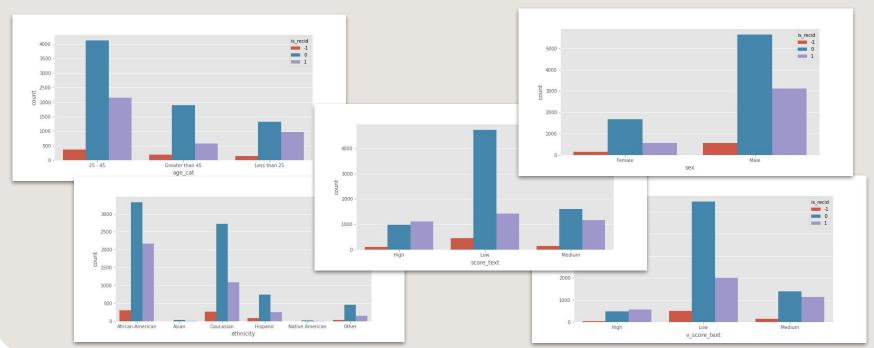
Data Exploration - Numerical Attributes

We have 16 numerical attributes. The following box plots, show better some linear values and few mainly characterized by outliers.



Data Exploration - Categorical Attributes

We have 31 non numerical attributes, most of them are text descriptions, identification codes, or dates. The most relative attributes are **sex**, **age_cat** and **race** (that we rename in **ethnicity** for moral reasons). Regarding the decile_score we decided to maintain the attributes **score_text** and **v_score_text**. The following plots shows the correlation between the categorical attributes and the class label:



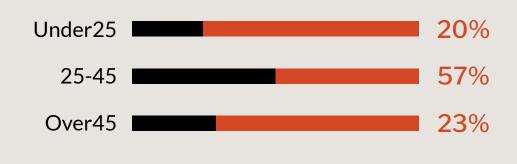
Data Exploration - Categorical Attributes x x

Gender and age





20%



Score Text



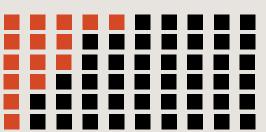


Medium



23%

Low 67% African-American Caucasian Hispanic Other Asian Native American



Ethnicity

10% 5% 0.5% 0.5%

50%

34%

16

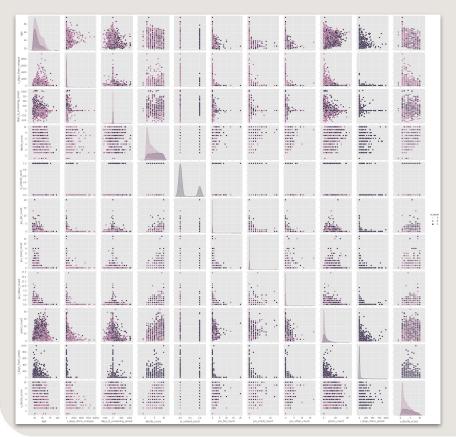
XX

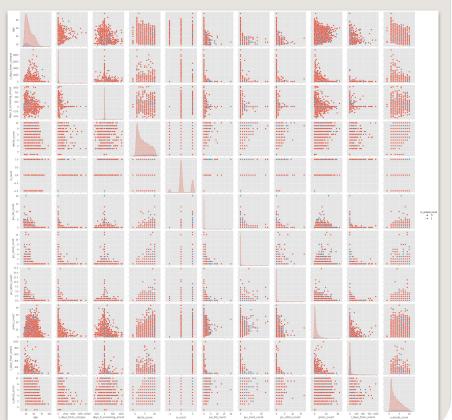
Data Exploration - Dates Attributes



About the **12 dates attributes**, since we noticed a **high variability**, we had some problems in plotting them in a sustainable time range. So, we decided to show, on the report, the **values_count()** and their statistics description in order to complete our Data Understanding report.

Data Exploration - Scatter Plots



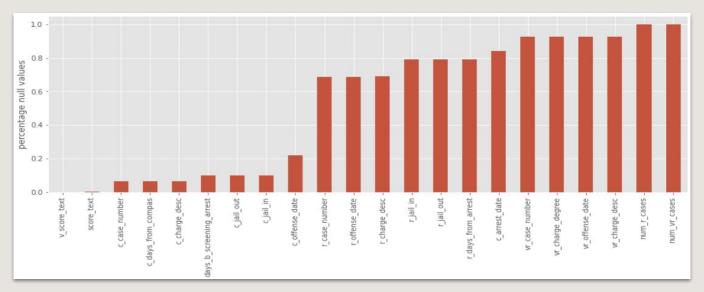


Data Exploration - Correlation Matrix



Data Quality - Null Values

The following plot shows the percentage of null values (>0%):



By analyzing the percentage of NULL values for each attribute, we intuitively saw that **num_r_cases** and **num_vr_cases** are useless for our analysis because they are totally NULL.

Data Quality - Inconsistent Values

Duplicated attributes

Another useless attribute is **decile_score.1** cause it is a duplicate, so we did not consider it for our analysis.

Incorrect values

- No coherence between name and the attributes first and last.
- Inconsistent values for the attribute **dob** (dates of birth) respect to the defendant's current **age** attribute.

Other considerations

• The attributes **is_recid** and **is_violent_recid** have only **0** and **1** as possible values. We will erase the record with values **-1** (assuming that this value indicates an unknown value).







Prepare our Dataset for the Modeling phase.

This is an important phase in which we can apply strategies and mechanism in order to select, clean and transform our data.







Data Selection

Based on the previous step done, we identified the most relevant information to reach our goal.



Included attributes

Included Attributes

- age_cat
- c_offensive_date
- is recid
- is violent recid
- r_offensive_date
- race
- sex
- score text
- v_score_text
- vr_offensive_date

We decided to delete the attributes:

- with high percentage of null values
- with high variability
- with inconsistency
- with outliers
- regarding dates
- less relevant to our analysis



Important Steps



Data cleaning

- **columns.difference()** to clean dataset.
- Some is recid value are "-1", assumed that are unknown values.
- Not binarized is recid and is violent recid.



We didn't integrate or merge anything in our dataset.

Formatted data



- Renamed race to **ethnicity** for ethical reason.
- Renamed the values of age_cat:
 - Less than 25 => young.
 - 25 45 = adult.
 - Greater than 45 => senior.

ata Integration

Data Construction



No need to add new data for the analysis.





Modeling

After the Data Understanding and the Data Preparation steps, we are ready to proceed with the Modeling phase.

Classifiers Description



Since we worked on a binary classification task and since the final dataset contains mainly categorical attributes, some of the most common algorithms used to solve this type of problem are the following:

Naïve Bayes Classifier

Naive Bayes classifiers are a collection of classification algorithms based on Bayes'
Theorem.

Random Forest Classifier

It is basically a set of decision trees (DT) from a randomly selected subset of the training set.

Decision Tree Classifier

A DT is a flowchart like tree structure with:

- nodes → test on an attribute;
- branches → outcome of the test:
- terminal nodes (leaves) → class label.

K-Nearest-Neighbors Classifier

It is non-parametric, that means no underlying assumptions about the distribution of data.



AdaBoost Classifier

AdaBoost classifier combines weak classifier algorithms to form strong classifiers.



Test Design

We splitted into Training Set and Test Set, respectively with a percentage of 75 and 25. Then we performed Undersampling or Oversampling in order to balance the recid dataset and the violent recid dataset.



Build Model

To find out the best parameters for each model's algorithm we used a function called GridSearchCV. The parameters of the estimator used to apply these methods are optimized by cross-validated grid-search over a parameter grid.





Model Assessment

We fitted the models and, based on the predictions set, we got the values of the quality measure: accuracy, recall, precision and F-measure. We decided to look at F-measure to select the best model for our dataset.

	recid dataset	violent recid dataset	
Naïve Bayes	Accuracy: 0.5934 Recall: 0.6670 Precision: 0.4315 F-measure: 0.5240	Accuracy: 0.5929 Recall: 0.3805 Precision: 0.2663 F-measure: 0.3133	
Decision Tree	Accuracy: 0.6402 Recall: 0.5816 Precision: 0.4707 F-measure: 0.5203	Accuracy: 0.5702 Recall: 0.3850 Precision: 0.2514 F-measure: 0.3042	
KNN	Accuracy: 0.3442 Recall: 0.9903 Precision: 0.3374 F-measure: 0.5033	Accuracy: 0.6771 Recall: 0.1593 Precision: 0.2483 F-measure: 0.1941	

	recid dataset	violent recid dataset	
Random Forest	Accuracy: 0.6380 Recall: 0.6151 Precision: 0.4699 F-measure: 0.5328	Accuracy: 0.5713 Recall: 0.3850 Precision: 0.2522 F-measure: 0.3047	
AdaBoost	Accuracy: 0.6369 Recall: 0.5838 Precision: 0.4671	Accuracy: 0.6199 Recall: 0.3584 Precision: 0.2812	
	F-measure: 0.5190	F-measure: 0.3152	





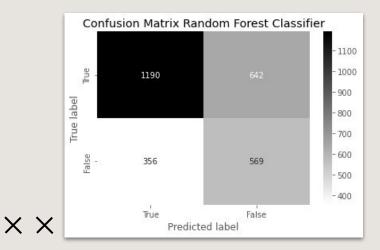
05 Evaluation

In this final phase, we evaluated the best model according to the previous steps.

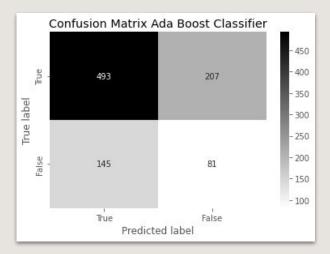
Results Evaluation

According to our results, the best models are the **Random Forest Classifier** (f-measure>0.53) for recid prediction and the **AdaBoost Classifier** (f-measure>0.30) for the violent recid dataset.

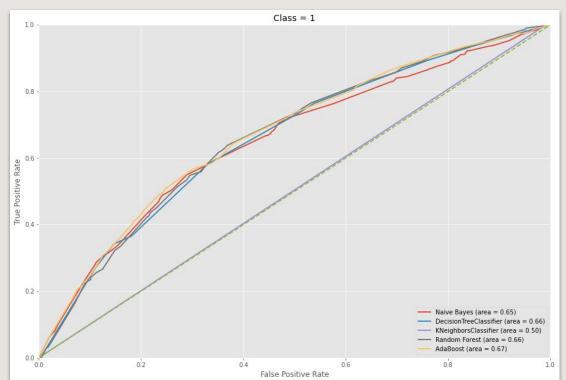
Recid Dataset



Violent Recid Dataset



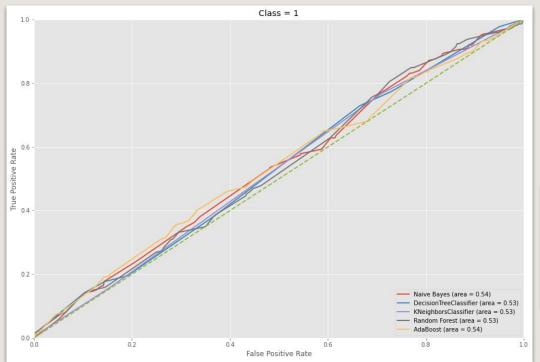
ROC Curve - Recidivism



Classification Report -		Random Forest Classifier		
	precision	recall	f1-score	support
0	0.77	0.65	0.70	1832
1	0.47	0.62	0.53	925
accuracy			0.64	2757
macro avg	0.62	0.63	0.62	2757
weighted avg	0.67	0.64	0.65	2757

Classification	n Report -	Ada Boost	Classifier	
	precision	recall	f1-score	support
0	0.76	0.66	0.71	1832
1	0.47	0.58	0.52	925
accuracy			0.64	2757
macro avg	0.61	0.62	0.61	2757
weighted avg	0.66	0.64	0.64	2757

ROC Curve - Violent Recidivism



support	Classifier f1-score		Report - precision	Classification
700	0.74	0.70	0.77	0
226	0.32	0.36	0.28	1
926	0.62			accuracy
926	0.53	0.53	0.53	macro avg
926	0.63	0.62	0.65	weighted avg

Classificatio	n Report -	Naive Baye	s Classifie	er
	precision	recall	f1-score	support
0	0.77	0.66	0.71	700
1	0.27	0.38	0.31	226
accuracy			0.59	926
macro avg	0.52	0.52	0.51	926
weighted avg	0.65	0.59	0.61	926

Sub goals

Predict the number of days from the first crime to the recid

offense date.

	coefficient
age_cat_senior	47.857954
age_cat_young	-17.088324
ethnicity_Asian	89.822557
ethnicity_Caucasian	-27.749853
ethnicity_Hispanic	-4.900140
ethnicity_Native American	-0.566236
ethnicity_Other	-6.337896
score_text_Low	26.047265
score_text_Medium	15,459139
sex_Male	-0.796888

coefficient age cat senior 124.789211 age cat young -8.889943 ethnicity Asian -42,569574 ethnicity Caucasian -75,149561 ethnicity Hispanic 45.466648 ethnicity Native American 364.672239 ethnicity Other -84.999001 v_score_text_Low -32,905414 v_score_text_Medium 23.736487 sex_Male -45.110255

Violent Recid Dataset

Recid Dataset

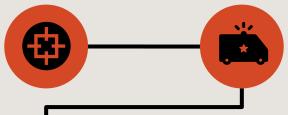
Meaning of the Coefficients

	××	Age Cat	Sex	Ethnicity	Score
	1st Dataset	young	male	caucasian	high
	2nd Dataset	young	male	other	low
		Age Cat	Sex	Ethnicity	Score
	1st Dataset	senior	female	asian	low
	2nd Dataset	senior	female	native american	medium

Process Review

Accuracy

We did not reach a high level of accuracy

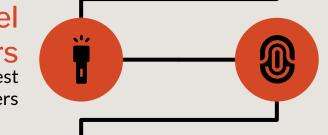


Other Models

Explore and analyze the datasets with more types of models

Model Parameters

Investigate and find best parameters



Predicting Days

Find a better way to explore linear regression models

Balance Dataset

Try to balance the datasets in a better way



Assessment

Try new statistics libraries and technologies

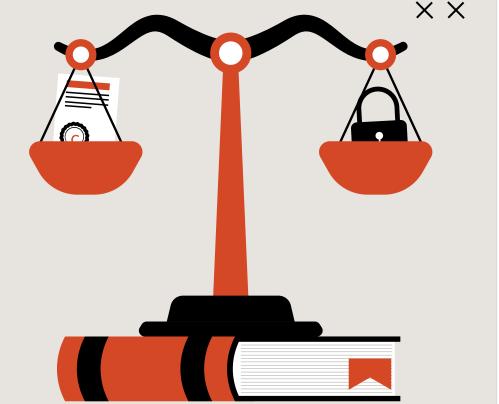


Conclusion

Since this dataset is not well studied in literature, we wanted to analyze it in a simple and readable way.

- We reached a discrete accuracy level (0.60)
- High biases present in this unbalanced dataset
- Represents a deeper social issue
- We analyzed different sub goal in order to explore different point of views
- Do our best to reach a high degree of inclusiveness for the wellness of the whole society

Thanks for your attention



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Data Analytics (Machine Learning) Project - a. y. 2021/2022