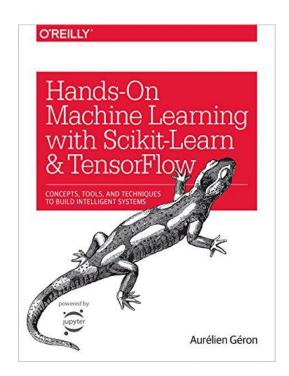
OSA Case Study

Gaining Intuition from Data

Sergio Pérez Morillo

Methodology

- 1. Framing the Problem
- 2. Wrangling the Data
- 3. Exploratory Data Analysis
- 4. Data Preparation
- 5. Model Testing & Fine-Tuning
- 6. Results & Model Comparison



Framing the Problem

1. Framing the Problem





1. Framing the Problem

Treatment

Forgetfulness

Snoring

Age

Definition

Discontent

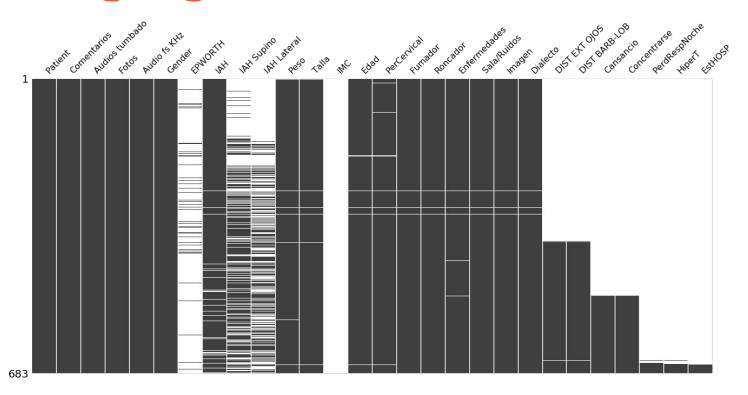
Somnolence

Symptoms

Diagnosis

Collar Size

Weight



Patient IAH Weight

Gender Age Height

Snorer Illness Smoker

Column

		200
	Patient	0
	Gender	0
	IAH	34
	Peso	8
	Talla	7
	Edad	8
	PerCervical	12
	Fumador	3
	Roncador	3
En	fermedades	5

Row

299 8

314 8

663 4

657 4

178 2

179 2

180 2

379 2

Numerical Features

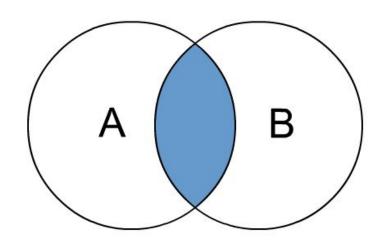
	Age	IAH	Cervical	Weight	Height	ВМІ
mean	49.50	20.39	40.64	87.73	171.28	29.86
std	12.39	18.60	3.96	18.36	9.56	5.62
min	20.00	0.00	30.00	45.00	144.00	18.29
25%	40.00	6.40	38.00	75.00	165.00	26.04
50%	49.00	14.40	41.00	86.00	171.00	28.73
75%	59.00	30.00	43.00	98.00	178.00	32.77
max	88.00	108.60	53.00	165.00	197.00	63.65

Categorical Features

Factures	Number of Categories		
Features	Original	Updated	
Gender	2	2	
Smoker	6	4	
Snorer	8	4	
Illness	249	3	

Classification Dataset

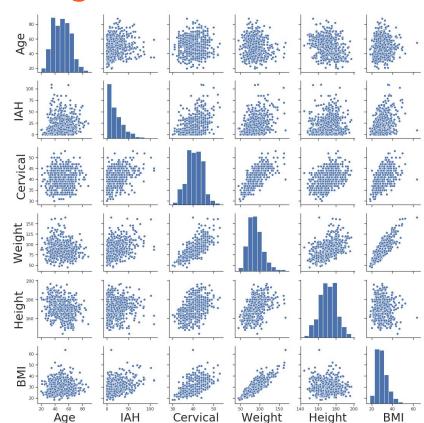
Category	Condition	Count
Severe	IAH >= 30	83
Healthy	IAH <= 10	91



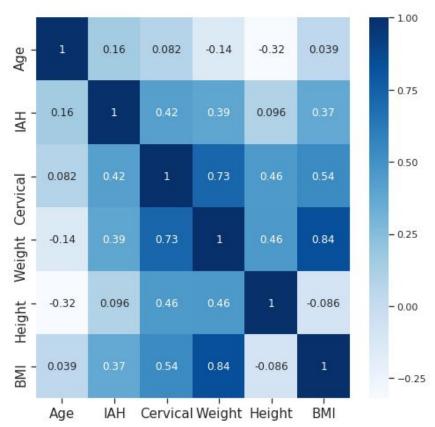
Target Feature

Inner Join

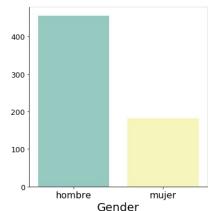
Numerical Features

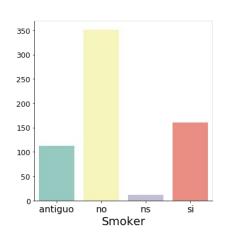


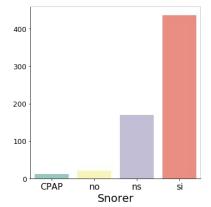
Numerical Features

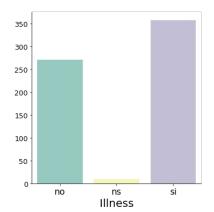


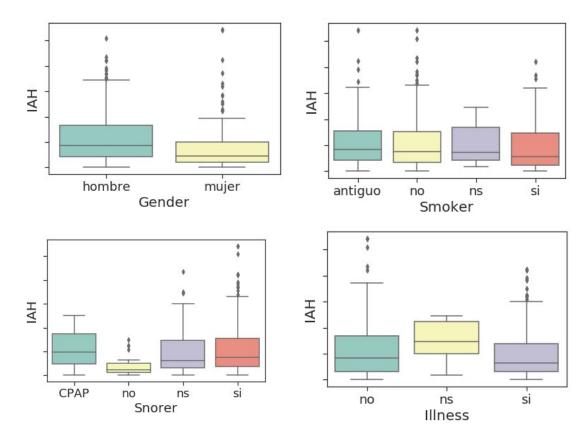
Categorical Features

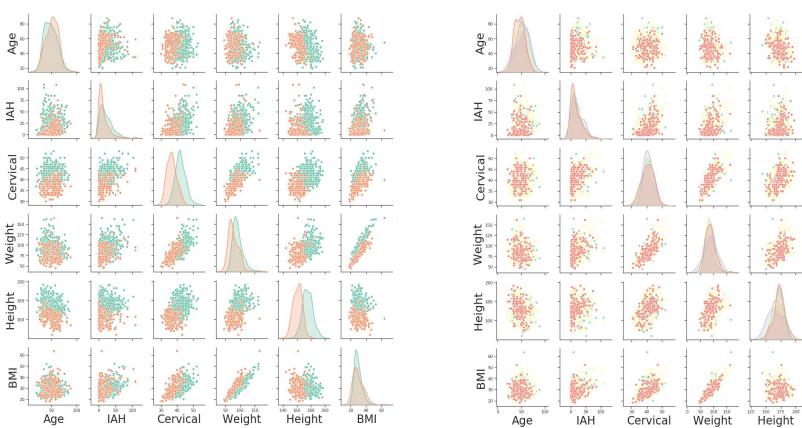












BMI

Data Preparation

4. Data Preparation

Data Transformation log(x+1), polynomials

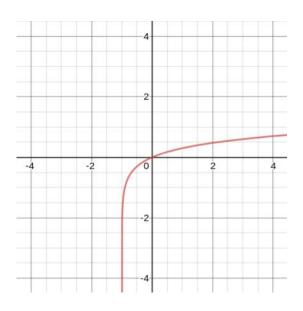
Data Scalingnormalization, standardization

Dimensionality Reduction PCA, t-SNE

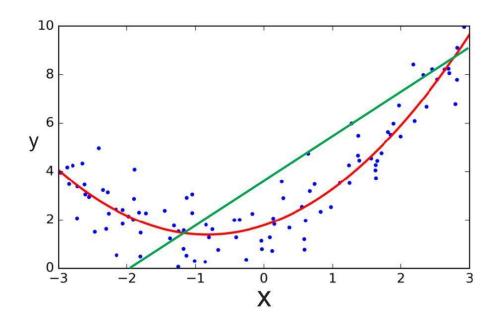
Feature Selection filtering, wrapping, embedded

4.1. Data Transformation

log(x+1)



Polynomial Features



4.2. Data Scaling

Normalization

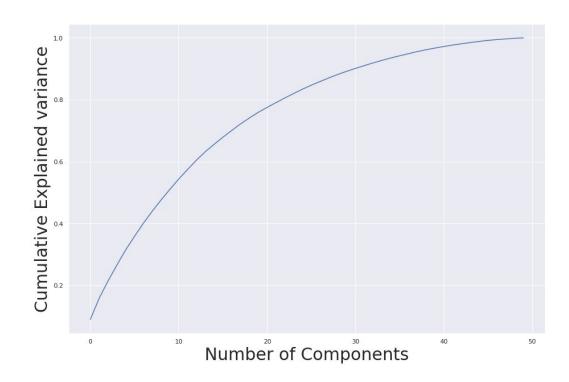
$$z = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Standardization

$$z = \frac{x - \mu}{\sigma}$$

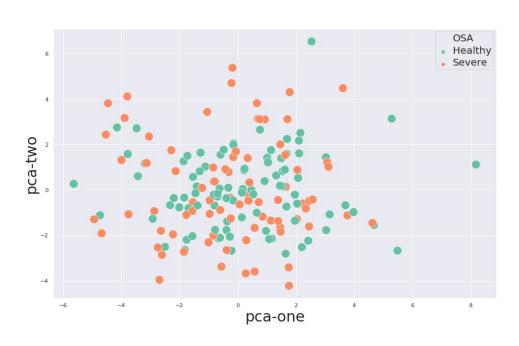
4.3. Dimensionality Reduction

PCA

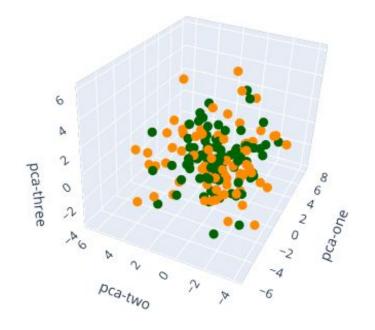


4.3. Dimensionality Reduction

2-Component PCA

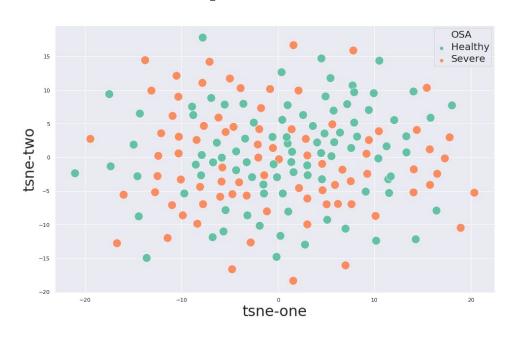


3-Component PCA

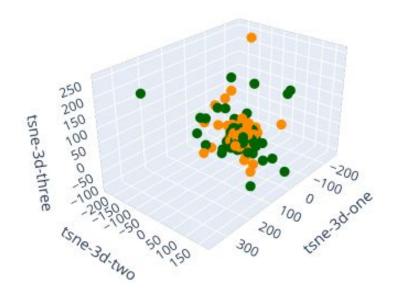


4.3. Dimensionality Reduction

2-Component t-SNE



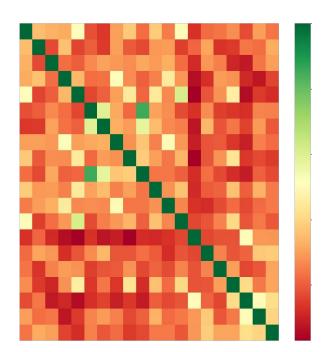
3-Component t-SNE



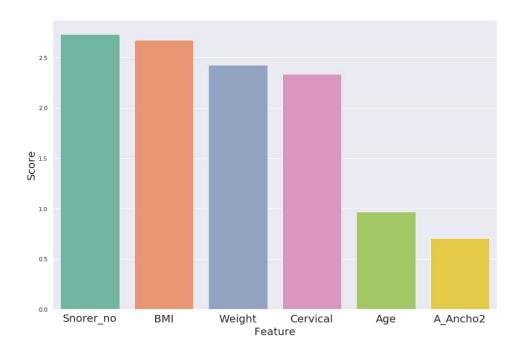
4.4. Feature Selection

Filtering

Pearson Correlation



Univariate Selection

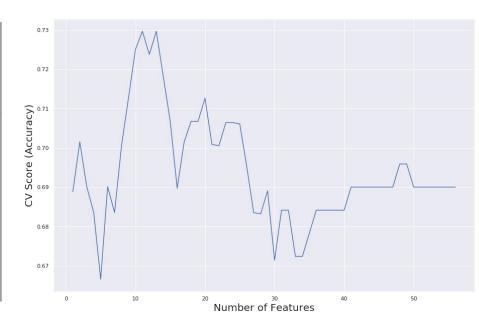


4.4. Feature SelectionWrapping

Recursive Feature Elimination (RFE)

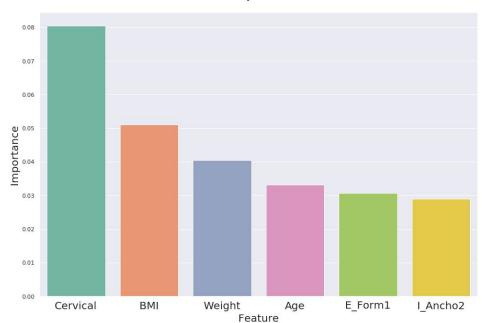
TOP FEATURES		
Importance	Feature	
Tier 1	A_Ancho2, Age, BMI, Cervical, Weight	
Tier 2	Snorer_no	
Tier 3	A_Form4, E_Form2	

CV-RFE



4.4. Feature Selection Embedded

Feature Importance



Select From Model

Top Features

Age

Cervical

Weight

A_Ancho2

Snorer_no

Model Testing & Fine-Tuning

Cross Validation

Stratified 10-Fold

Hyperparameter Tuning

Grid Search

Evaluation Metrics

Regression

$$ext{MAE} = rac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

Classification

Precision

Recall

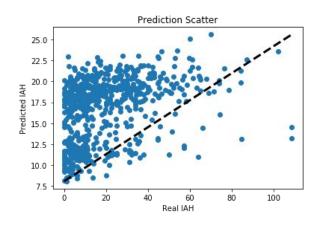
f1-score

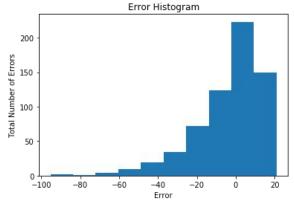
Accuracy

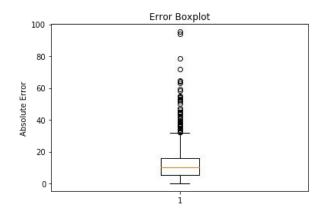
roc-auc score

Evaluation Metrics

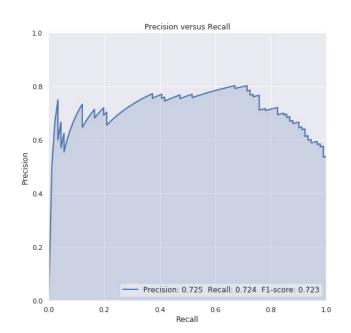
Regression

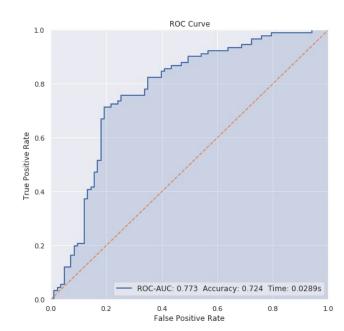






Evaluation Metrics





Modeling - Classical Models

Regression

Model	Hyperparameters
Linear Regression	-
Stochastic Gradient Descent (SGD)	Loss Function, Penalty.

Model	Hyperparameters
Logistic Regression	C, Penalty, Solver.
Stochastic Gradient Descent (SGD)	Loss Function, Penalty.

Modeling - Regularizers

Regression

Model	Hyperparameters
Lasso	Alpha
Ridge	Alpha, Solver.
ElasticNet	Alpha, L1-ratio.

Model	Hyperparameters
Ridge	Alpha, Solver.

Modeling - K-Nearest Neighbors

Regression

Model	Hyperparameters
Nearest Neighbors	Number of neighbors
Radius Neighbors	Radius

Model	Hyperparameters
Nearest Neighbors	Number of neighbors

Modeling - Naive Bayes

Regression

Model	Hyperparameters
-	-

Model	Hyperparameters
Bernoulli	Alpha
Gaussian	-

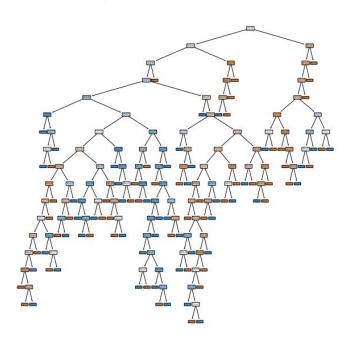
Modeling - Tree-based Models

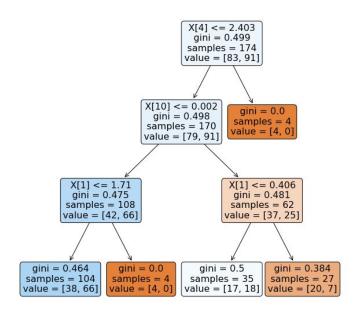
Regression

Model	Hyperparameters
Decision Trees Extra Trees	Max depth, max leaf nodes, min samples leaf, min samples split.

Model	Hyperparameters
Decision Trees Extra Trees	Max depth, max leaf nodes, min samples leaf, min samples split.

Modeling - Tree-based Models





Modeling - Ensemble Models

Regression

Model	Hyperparameters
Bagging	Number of estimators,
Random Forest	max samples,
Adaboost	learning rate (Adaboost &
GradientBoosting	XGBoost).
XGBoost	

Model	Hyperparameters
Bagging	Number of estimators,
Random Forest	max samples,
Adaboost	learning rate (Adaboost &
GradientBoosting	XGBoost).
XGBoost	

Modeling - Support Vector Machines

Regression

Model	Hyperparameters
SVR Linear	C, Epsilon.
SVR Nonlinear	Kernel, C, Epsilon.

Model	Hyperparameters
SVC Linear	С
SVC Nonlinear	Kernel, C.

Modeling - Neural Networks

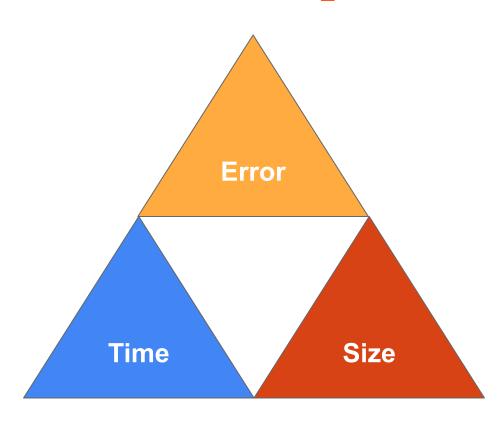
Regression

Model	Hyperparameters
MLP	Neurons, layers, activation function, solver function.

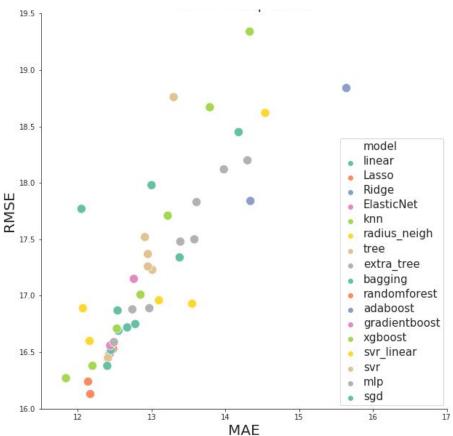
Model	Hyperparameters
Perceptron	Penalty, early stopping.
MLP	Neurons, layers, activation function, solver function.

Results & State of the State of

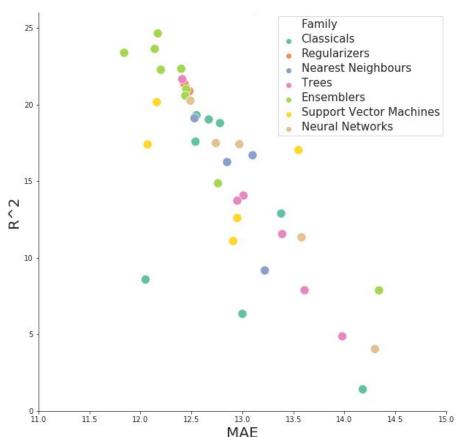
5. Results & Model Comparison



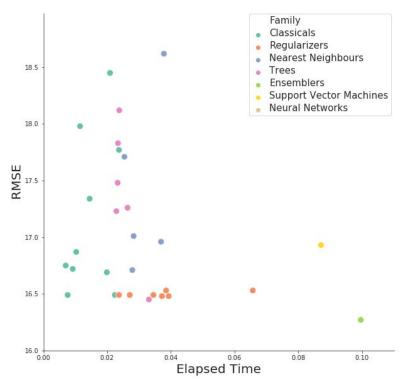
MAE vs. RMSE

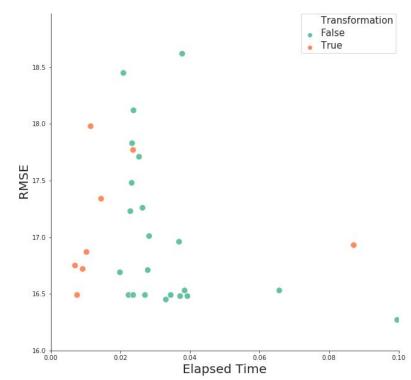


MAE vs. R²

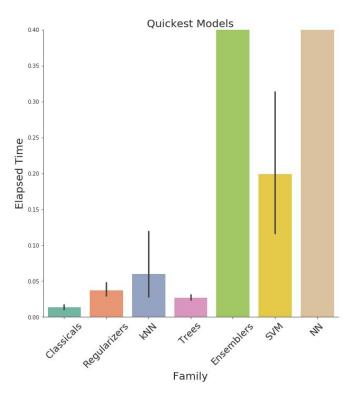


Elapsed Time vs. RMSE



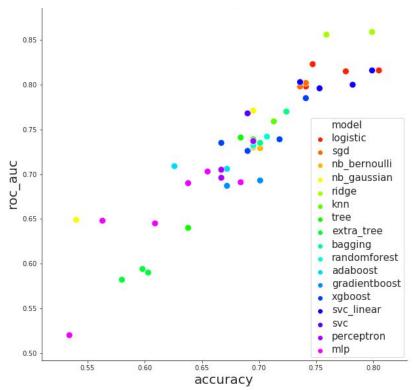


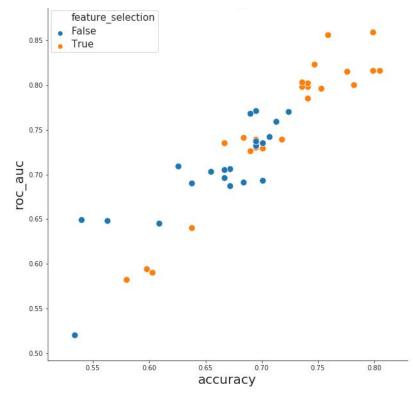
Elapsed Time



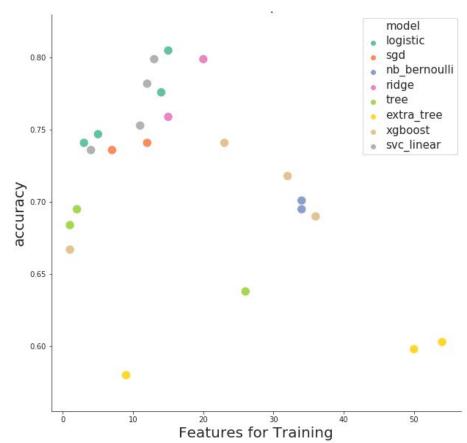


Accuracy vs. ROC-AUC

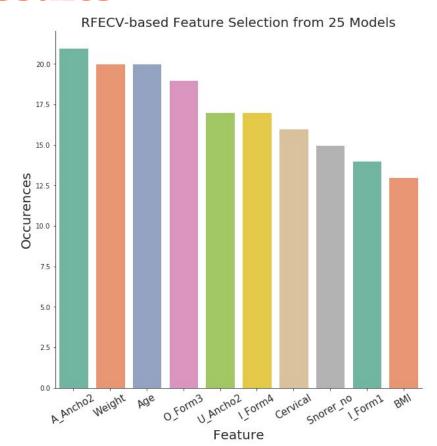




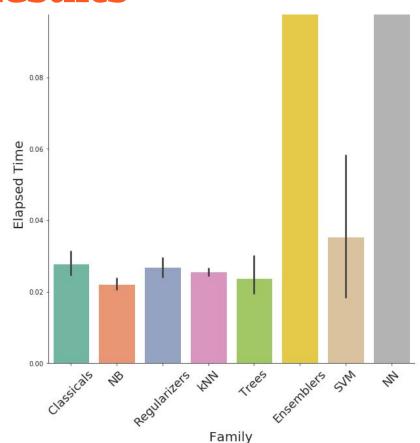
Accuracy vs. Features used in training



Most Important Features



Elapsed Time



Conclusions

6. Conclusions

The data were not sufficient for a real scenario, hence all models are underfitted. More data is necessary.

The most important features were highlighted in several steps of the methodology using different approaches.

Small models were almost as good as large models but much quicker. Feature Selection (CV-RFE) played a big role.

Questions?

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