Data challange

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Outline

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2. Data Analysis
   - Data exploration
   - Unbalanced data
3. Model design
4. Performance
5. Conclusions

Introduction

Data Analysis

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Introduction

What's the problem?

- Multi class classification of Cardiotocographic data of Fetal Heart Rate (FHR)
- Classes:
  1. **Normal** (N)
  2. **Suspect** (S)
  3. **Pathologic** (P)
- 21 features describing measuraments of Cardiotocographic measured by **SisPorto** system.
- Click here to download data

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Data Analysis

Data exploration

Features can be dived into 3 groups:

1. **Signal histogram properties**: Width, Min, Max, Nmax, Nzeros, Mode, Mean, Median, Variance, Tendency
2. **Signal global properties**: LB, AC, FM, UC, ASTV, mSTV, ALTV, mLTV
3. **Deceleration properties**: DL, DS, DP

All features are numerical except for **DS** that is binary.

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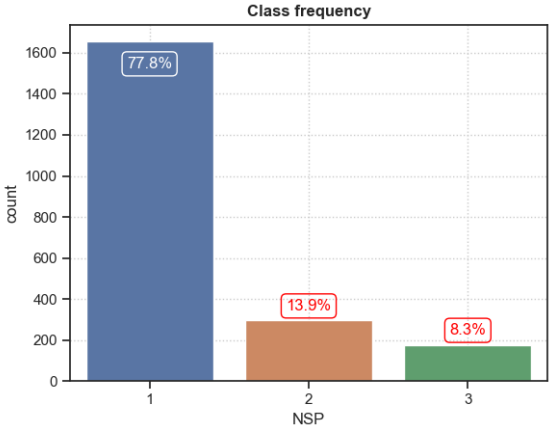
Class frequency



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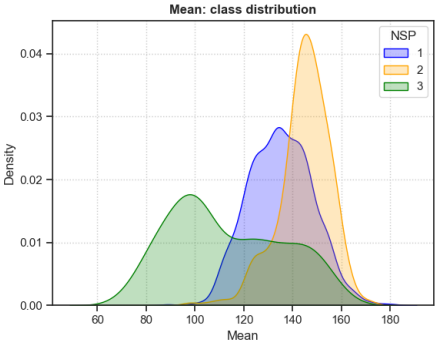
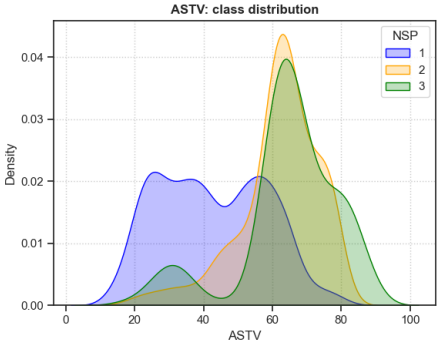
Features selection

Single variable distribution





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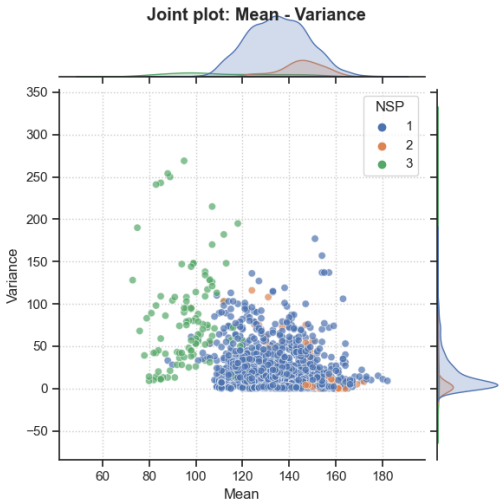
Joint distribution



Features selection

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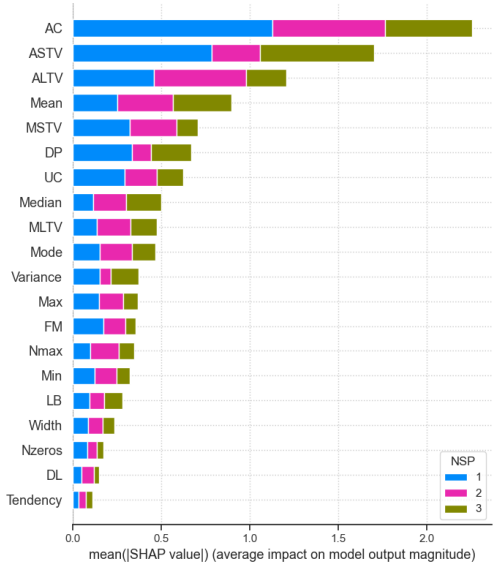
Conclusion

From graphical exploration we deduce that **AC**, **ASTV**, **ALTV**, **Mean**, **Variance**, **DP** will be the main regressors.

Features selection

Shapley value



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Shapley values confirm the graphical analysis. The main regressors will be: **AC, ASTV, ALTV, MSTV, Mean, Variance, DP**.

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Unbalanced data

We must take care of unbalanced data to avoid models overfitting the most frequent class (**N**).

We adopt two different techniques:

- **Sample weight** applied to cost function.
- Oversampling via `SMOTE` algorithm.

Unbalanced data

Sample weight

We build a weight k_i for each class i to compensate data asymettry in the following way:

Formula:

$$c_i = \#\{\text{samples of class } i\}$$

$$K = \frac{1}{c_1} + \frac{1}{c_2} + \frac{1}{c_3}$$

$$k_i = \frac{K}{c_i}$$

Results:

$$k_1 = 0.06 \pm 0.002$$

$$k_2 = 0.35 \pm 0.0016$$

$$k_3 = 0.59 \pm 0.0013$$

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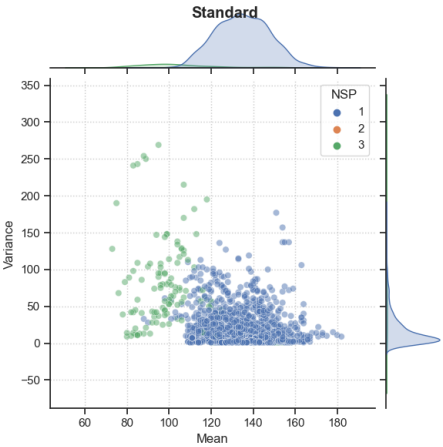
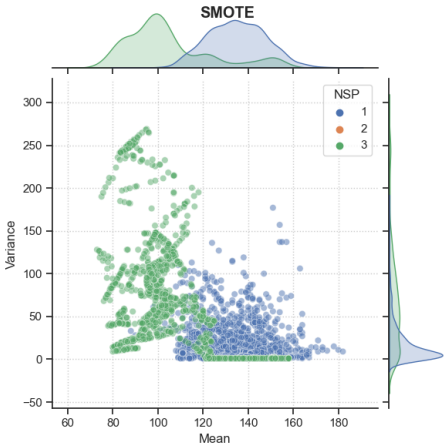
SMOTE





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Benchmarks

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Benchmark models:

- `MostFrequent`: always predict most frequent class in training set.
- `SmartRandom`: predict extracting random class with a probability equal to frequency of the class in training set.

Model design

Models

- `Logistic`
- `LogisticWeight`: logistic model trained on weighted data
- `CatBoost`
- `CatBoostWeight`: Boosted Tree model trained on weighted data
- `CatBoostSMOTE`: Boosted Tree model trained on augmented data via `SMOTE` algorithm.

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Models

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Note

- `StandardScaler` has been applied on top of `Logistic` models due to L^1 regularisation.
- Early stopping have been appliead to `Boosted Tree` models to avoid overfitting.
- `RandomUnderSample` have been applied on top of `SMOTE` algorithm as suggested in the original paper.

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Metrics... which one?

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Nice to have properties:

- **Recall** score of class **P** as high as possible.
- Minimization of **False Negative** of classes **P** predicted as **N**.
- Reasonable **Precision** of classes **N** and **S** to avoid too much **False Positive**.

Performance

Metrics... which one?

Custom performance criteria

1. Choose the 3 models with best average **F2** score.
2. Among selected models choose the one with the highest **Recall** score of class **P**.

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Performance

Performance computed using `StratifiedCrossValidation` with `cv=5`:

Model	F2 Score	Recall class P
MostFrequent	0.315	0
SmartRandom	0.322	0.094
Logistic	0.712	0.678
LogisticWeight	0.755	0.785
CatBoost	**0.801**	0.795
CatBoostWeight	**0.797**	0.812
CatBoostSMOTE	**0.797**	**0.818**

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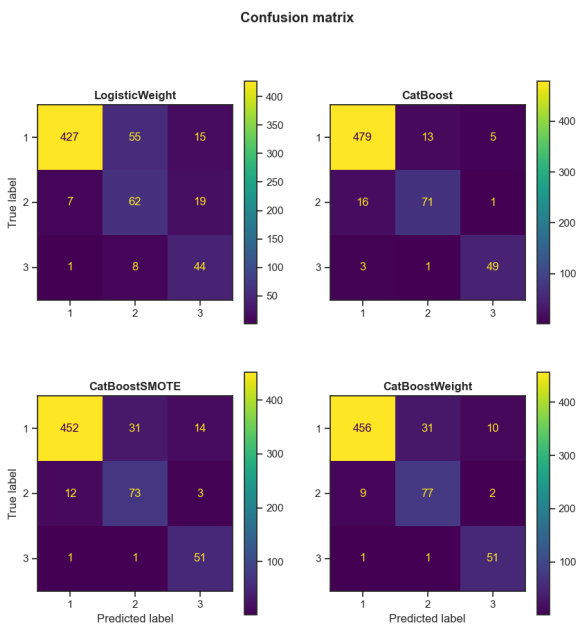
Confusion matrix
LogisticWeight
CatBoost
CatBoostSMOTE
CatBoostWeight
True label
Predicted label
427 55 15
7 62 19
1 8 44
479 13 5
16 71 1
3 1 49
452 31 14
12 73 3
1 1 51
456 31 10
9 77 2
1 1 51
1 2 3
400 350 300 250 200 150 100 50

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Conclusions

- Non linear models are necessary to fully exploit this problem and overperform linear model.
- Both data augmentation and sample weight contribute to performance improvement, in particular in term of **Pathologic Recall**.

Best model

Even if `CatBoostSMOTE` is the best model according to our criteria **I would choose** `CatBoostWeight` **as best model** because the two models have very close performance but the first one has a random component not fully controllable.

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Fin.