CSCI6917: Guided Research Methods

Summer 2023

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Exploring Class Imbalance Solutions: Investigating the Effectiveness of Data Balancing Techniques on Model Performance

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Project Objective

Purpose of this project is to answer to following questions:

- How different balancing techniques affects model performance?
- When we need to balance our data?
- Do we even need balancing?
- How balancing affects generalization capability of model?
- Which balancing techniques are effective?

In total, 96 models were built with 5 different balancing techniques and 1 baseline model.

Project Objective

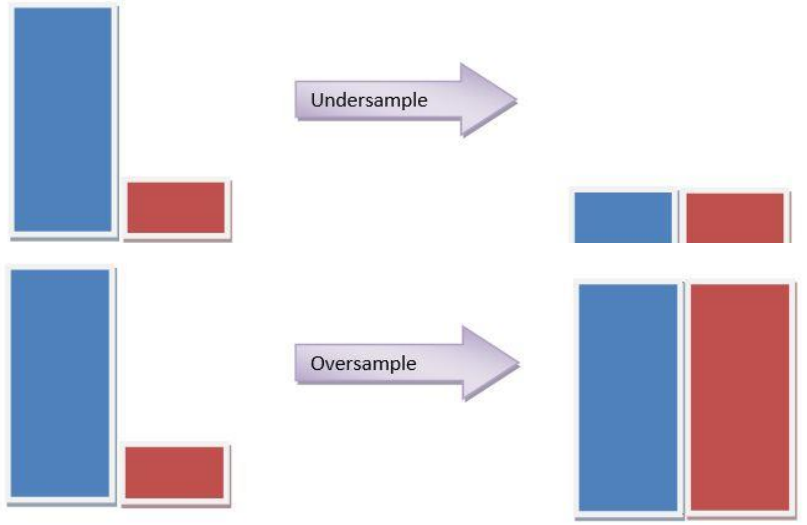
- **How is it done today?**
  - Basic data balancing techniques (upsampling, downsampling, SMOTE) are commonly used to address class imbalance.
  - However, the effectiveness of these techniques is often based on trial and error rather than a comprehensive evaluation.
- **What is new?**
  - Insights on technique effectiveness, class imbalance percentage impact, and overfitting risks.
- **Who will benefit from the work? Why?**
  - Researchers and practitioners dealing with imbalanced datasets.
  - Practical guidance for selecting appropriate balancing techniques and utilizing LightGBM's built-in balancing.
  - Informed decisions to enhance model performance in real-world applications efficiently.

Project Objective

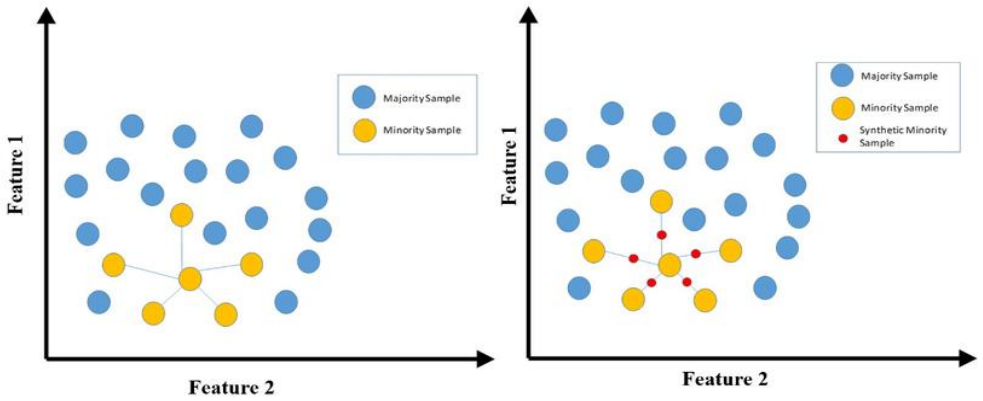
- Comprehensive Evaluation with Real and Synthetic Datasets
- Focus on Class Imbalance Percent
- Focus on Class Imbalance Percent
- LightGBM's Built-in Balancing Advantages

Technical Approach

- Collection of Data
- Data Preprocessing
- Building Baseline Model
- Applying Balancing techniques to the data
  - Upsampling
  - Downsampling
  - SMOTE
  - BalancedBaggingClassifier
  - Algorithm built-in balancing
- Analyze model results:
  - F1-Score
  - AUC



Downsample and Upsample



SMOTE

Technical Approach : Data

- During the research 13 different imbalanced datasets collected
- Different minority class percentages will show how balancing techniques performs in different degrees of imbalance
- Applied preprocessing steps:
  - Redefining target if needed
  - Encoding the categorical variables
  - Correcting type inconsistencies
  - Imputing missing values if needed

Dataset_Name	Row_Count	Minority_Class_Percent	Target_Column
Fraud	284807	0.172	Class
Fraud2	250000	0.5	is_fraud
Wine	6497	3.76	target
~~Letter-a~~	~~20000~~	~~3.94~~	~~letter_a~~
Abalone	1477	4.52	target
Pendigits	10992	9.59	is_9
Sick_euthyroid	2194	10.05	target
Covertype	581012	14.77	target
~~Letter-vowel~~	~~20000~~	~~19.39~~	~~is_vowel~~
Contraceptive	1743	22.6	target
~~Splice-junction~~	~~3186~~	~~24.07~~	~~target~~
Adult	32561	24.08	target
Churn	7043	26.53	target

Technical Approach : Data

- Problems in collected datasets:
  - Easier classification problems
  - Size of datasets
  - Nature of the data affects metrics
- Additional synthetic data generated:
  - Class distribution: 30%/70%
- By taking samples from this dataset, 5 more datasets generated

```
X, y =
make_classification(
    n_samples=200000,
    n_features=10,
    n_informative=7,
    n_classes=2,
    random_state=42,
    weights=[0.7,0.3],
    hypercube=False,
    class_sep=0.01,
    flip_y=0.15
)
```

Dataset	Minority_Class
Synthetic	0.3
Synthetic_20	0.2
Synthetic_10	0.1
Synthetic-5	0.05
Synthetic-1	0.01
Synthetic-0.5	0.005

Technical Approach : Model

LightGBM is a gradient boosting framework that utilizes a tree-based learning algorithm to construct powerful ensemble models. It offers several advantages that make it well-suited for imbalanced classification tasks.

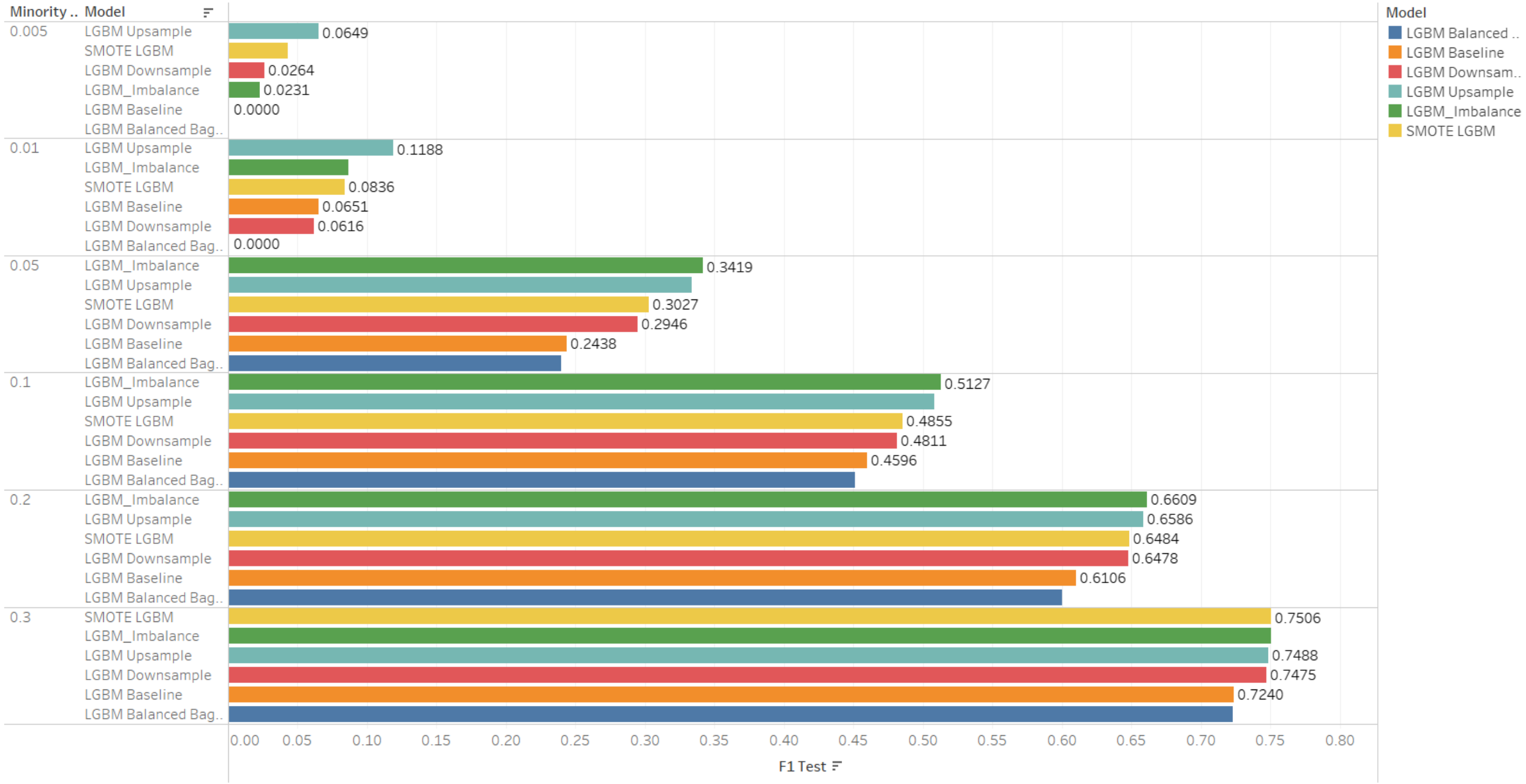
Why LightGBM?

- Built-in imbalance technique
- Doesn’t need a lot of preprocessing
- Boosting models generally performs better

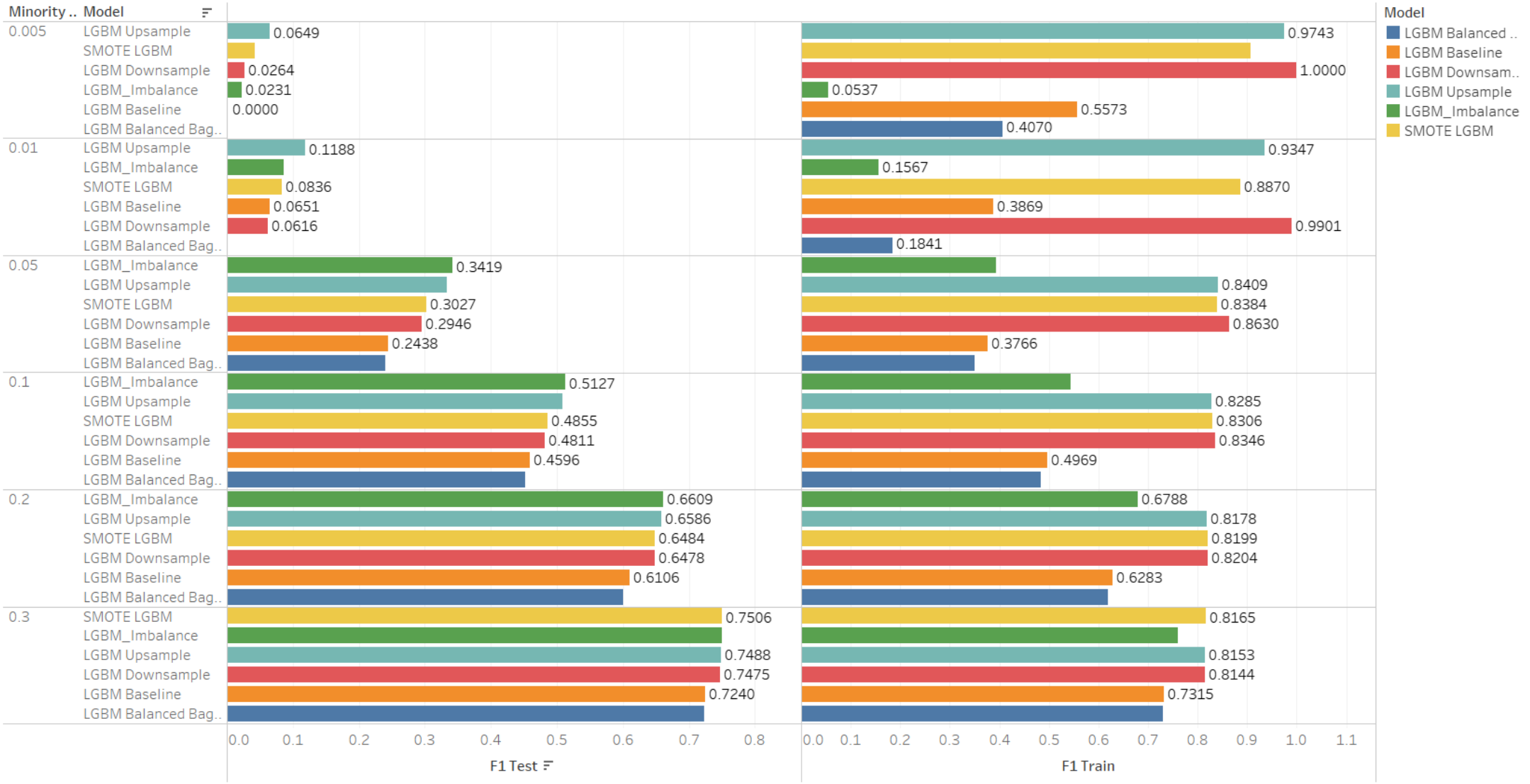
Models:

- LGBM Baseline
- LGBM Upsample
- LGBM Downsample
- SMOTE LGBM
- LGBM Balanced Bagging
- LGBM_Imbalance

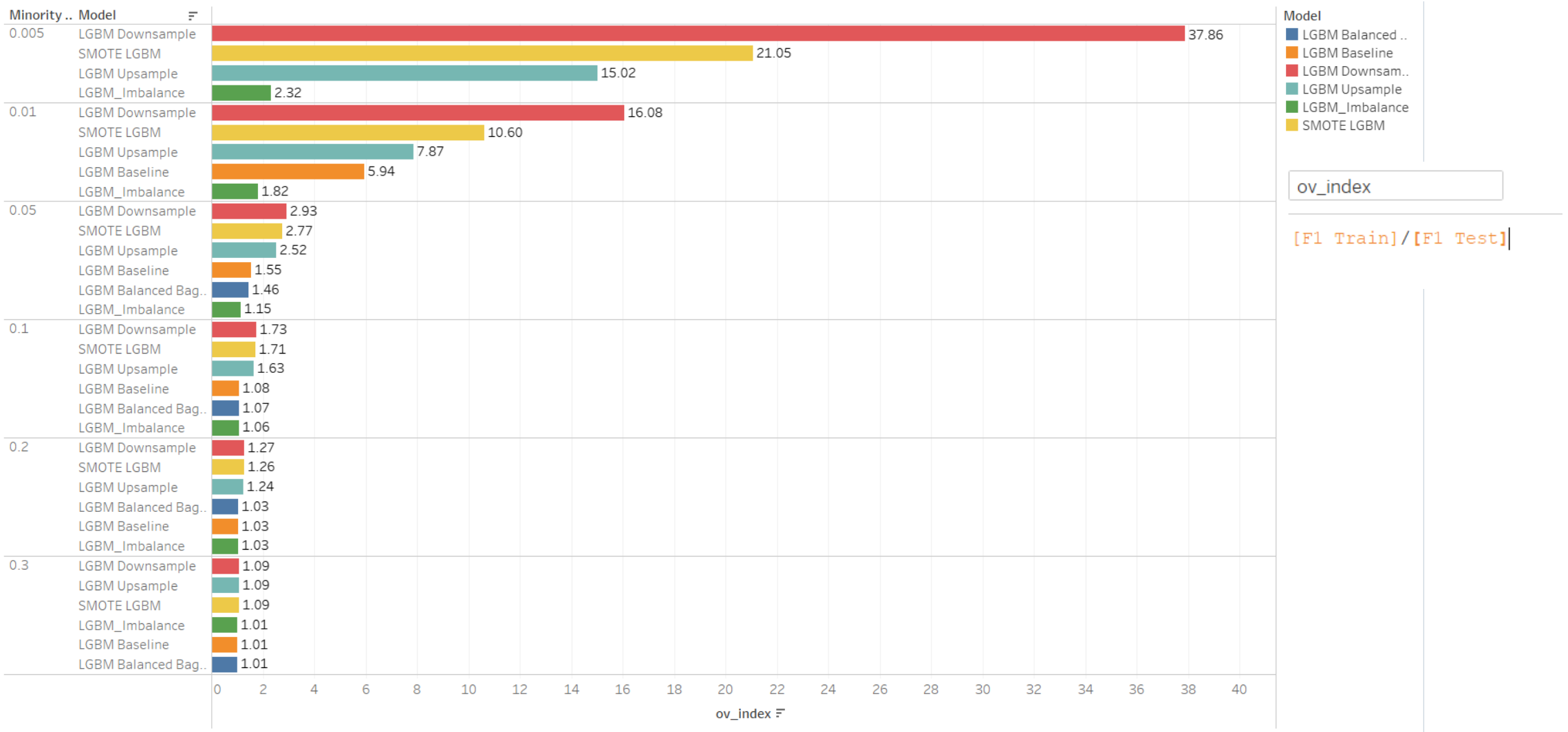
Results : F1-Scores on test data



Results : Overfitting

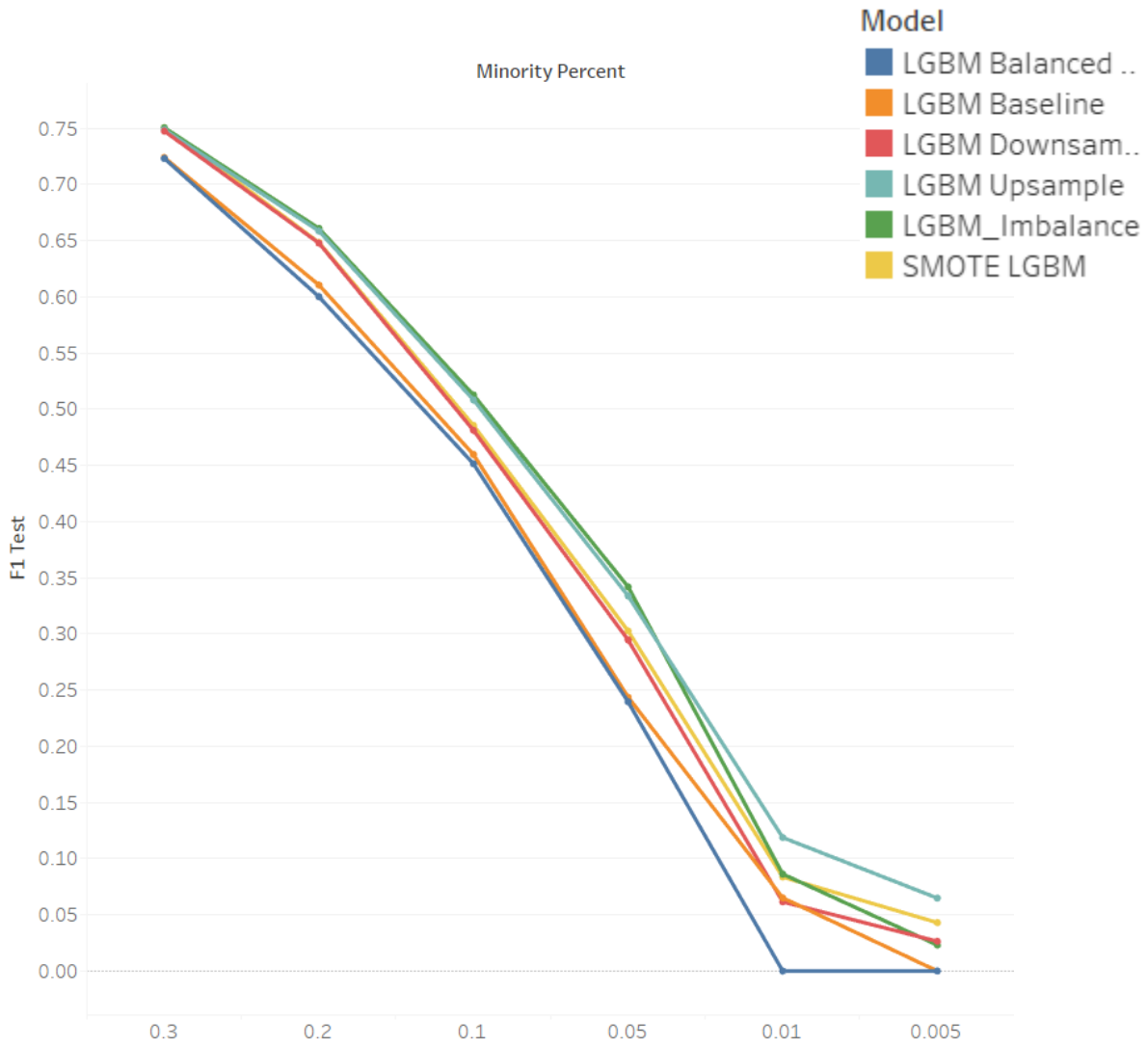


Results : Overfitting



Results


Minority Percent
AUC test
0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
0.72
0.70
0.68
0.66
0.64
0.62
0.60
0.3
0.2
0.1
0.05
0.01
0.005


Minority Percent
F1 Test
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0.3
0.2
0.1
0.05
0.01
0.005
Model
LGBM Balanced ..
LGBM Baseline
LGBM Downsam..
LGBM Upsample
LGBM_Imbalance
SMOTE LGBM

Conclusion

- When working with imbalanced dataset always build baseline model without any balancing technique
- We observed that balancing techniques are not very effective with class imbalance percent > 10%
- Some balancing techniques, especially downsampling, SMOTE and upsampling can cause overfitting
- LGBM’s built-in balancing generalizes data better than above techniques

Future Work

- Extending research with:
  - More broad datasets
  - More balancing techniques
  - Tests on different algorithms
- Calibrating models trained on balanced data
- Explaining mathematically reasons behind conclusions

Any Questions?