

The background is a vibrant, abstract composition of various colors and textures. It features broad, expressive brushstrokes in shades of blue, green, and yellow. Interspersed among these are patterns of small, dark blue dots and larger, irregular shapes in light blue and yellow. The overall effect is dynamic and artistic, resembling a modern digital painting.

# Marketing Targets

--- Customer Subscription Prediction

-- By Xufei Li

# Problem:

## Client: a Portuguese banking institution

- “Term deposits” - a major source of income
- Direct marketing campaigns (phone calls)
- Goal - predict if the customer will convert.

Data: Kaggle - [Banking Dataset - Marketing Targets](#)

(Train :45,211 rows; Test: 4,521 rows)



1

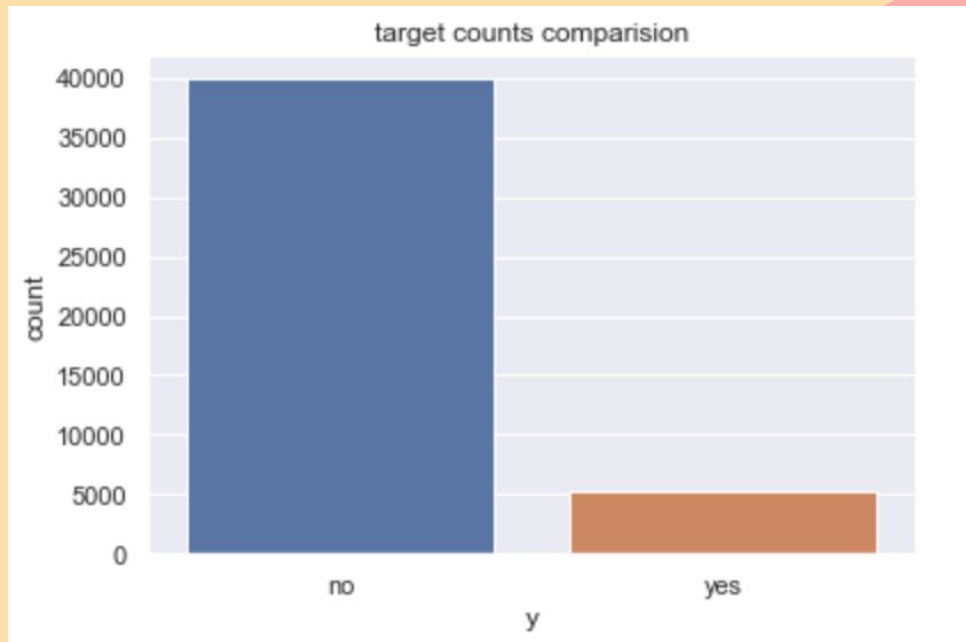
# Data Cleaning & EDA

# Data Cleaning & EDA

Drop “duration” feature

[Link for the reason](#)

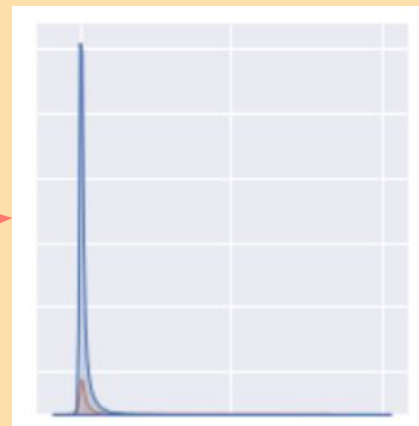
Class imbalance:  
Oversampling



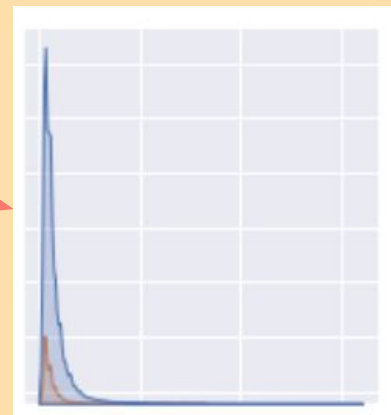
# EDA



“balance”



“campaign”

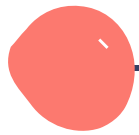




2

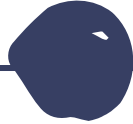
Modeling

# Workflow



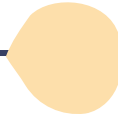
## Metric Choosing

F-beta(beta = 2)  
ROC\_AUC



## Baseline model

Logistic regression



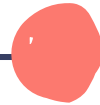
## Model Selection

6 model's comparison



## Retrain Model

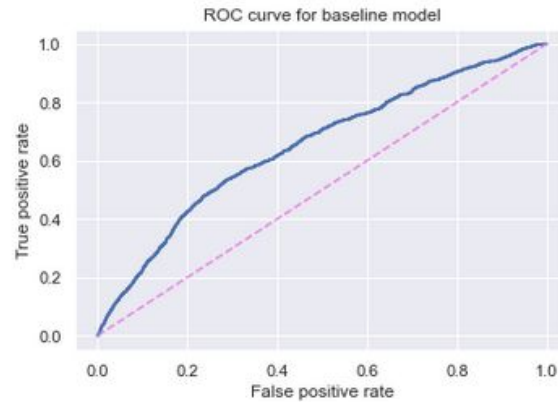
Retrain on (train+val)



## Model evaluation & Interpretation

# Baseline Model

Features: numerical features only - age, balance, day, campaign, pdays, previous



**F-beta: 0.7582**  
**ROC\_AUC: 0.6502**





# Improving Baseline Model

**Baseline Model**

**+ Scaling**

**+ Feature Engineering**

**F-beta: 0.7933**

**ROC\_AUC: 0.7687**

# Candidate Models

Baseline model:  
F-beta: 0.7582  
ROC\_AUC: 0.6502

F-beta(beta = 2)

0.7933

0.7632

0.8333

0.8329

0.8016

0.8388

Logistic  
Regression

20-NN

Random  
Forest

XGBoost

Naive  
Bayes

SVM

0.7687

0.7392

0.7928

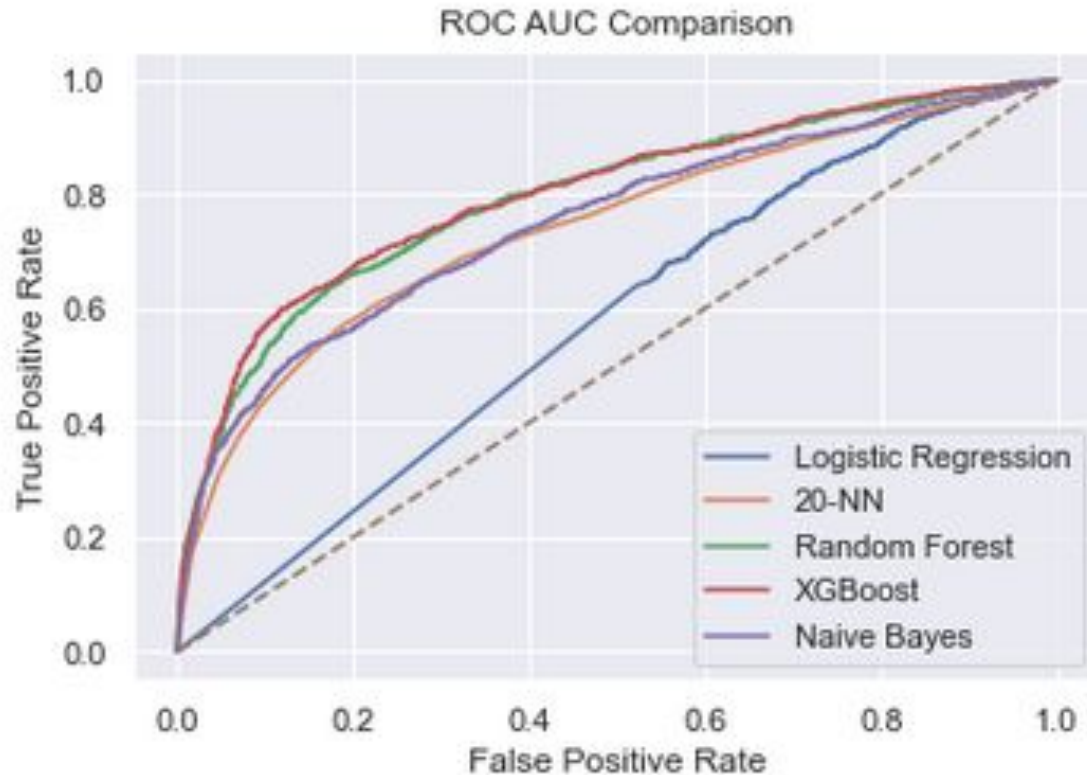
0.7992

0.7487

N/A

ROC\_AUC

# ROC\_AUC curve comparison



**Winner: XGBoost**

# Final Model - XGBoost

Current performance:

**F-beta:** 0.8329

ROC AUC: 0.7992

**Step 1: Tuning hyperparameter for XGBoost**

Best score on val:

**F-beta: 0.8536**

ROC\_AUC: 0.7983

**Step 2: Retrain model with (train+val) data**

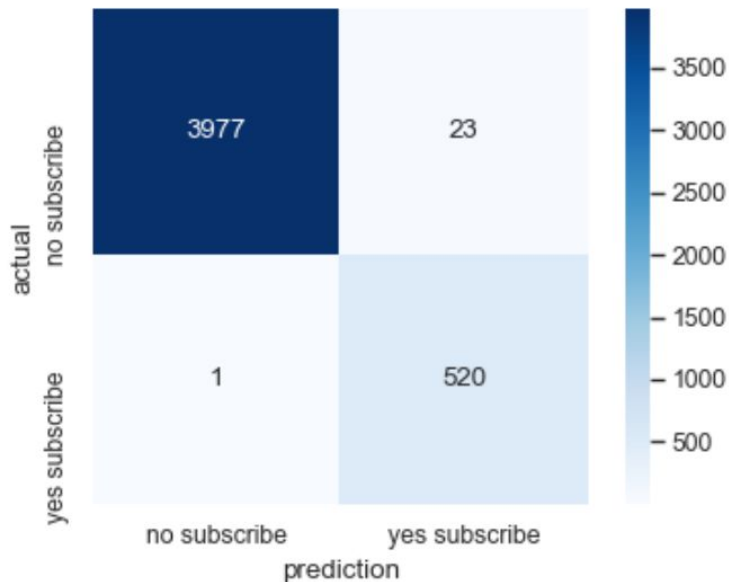
Final Score on Test:

**F-beta: 0.9946**

ROC\_AUC: 0.9998

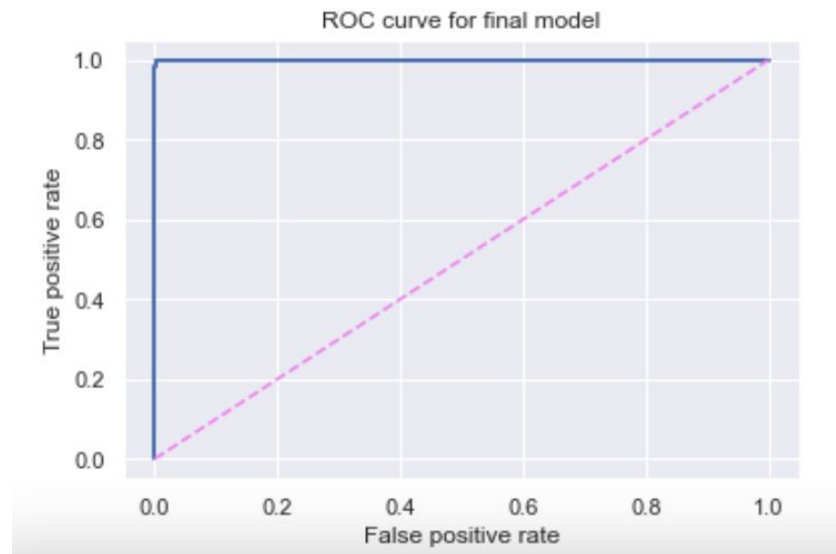
# Model Evaluation & Interpretation

Hard Prediction



**Perfect Classifier???**

Soft Prediction



# Future Work

1. Double check the code settings
2. Try different random\_state (validation?)
3. Try Random Forest to see if get similar result
4. Tuning hyperparameters for SVM to see how good it can be.

# Appendix 1: Final Model

```
gbm2 = xgb.XGBClassifier(  
    n_estimators=10000,  
    max_depth=11,  
    objective='binary:logistic', #new objective  
    learning_rate=0.05,  
    subsample=.8,  
    min_child_weight=2,  
    colsample_bytree=.8  
)  
  
eval_set=[(X_tr_rs, y_tr_rs),(X_test_dum,y_test)] #using test set  
fit_model = gbm2.fit(  
    X_tr_rs, y_tr_rs,  
    eval_set=eval_set,  
    eval_metric='auc', #new evaluation metric: classification error (could also use AUC, e.g.)  
                    #can "eval_metric" be F-beta score  
    early_stopping_rounds=20,  
    verbose=False  
)  
  
y_pred_test = gbm2.predict(X_test_dum, ntree_limit=gbm2.best_ntree_limit)  
y_prob_pred_test = gbm2.predict_proba(X_test_dum)[:,-1]  
  
print(f"train f-beta score: {fbeta_score(y_tr_rs,gbm2.predict(X_tr_rs),average='weighted',beta = 2)}")  
print(f"train ROC_AUC score: {roc_auc_score(y_tr_rs,gbm2.predict(X_tr_rs))}")  
  
print(f"test f-beta score: {fbeta_score(y_test,y_pred_test,average='weighted',beta = 2)}")  
print(f"test ROC_AUC score: {roc_auc_score(y_test, y_prob_pred_test)}")
```

```
train f-beta score: 0.9967927081981969  
train ROC_AUC score: 0.7477706527729072  
test f-beta score: 0.9946969122222279  
test ROC_AUC score: 0.9998795585412668
```