betsson group

Predicting future calls to the Customer Service

Application for CRM & VIP Data Scientist

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April 2024

Agenda

1

Introduction

- Business context
- Delivered files

2

Exploratory Data Analysis

- Statistical analysis
- Feature selection

3

Predictive modeling

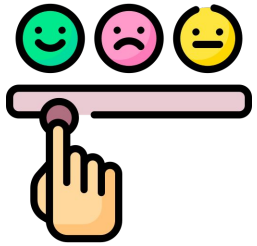
- Model selection
- Model validation
- Model deployment

How does it help the business?

Business context

For efficiency purposes, Betsson is trying to predict which customers are going to call the Customer Service, based on their past behaviour.

For a given day, predict whether a customer will call the Customer Service in the following 14 days.

Why? → **Optimize** customer relationship → 

therefore reducing churn

File delivery structure

project_folder

- **notebooks**
  - 0-eda-ipynb
  - 1-feature-selection.ipynb
  - 2-predictive-modeling.ipynb
  - pycaret.ipynb
- requirements.txt

GitHub repositories:

- Project (main)
- Streamlit App
- FastAPI

Docker hub (images):

- Streamlit App
- FastAPI

APP/API endpoints:

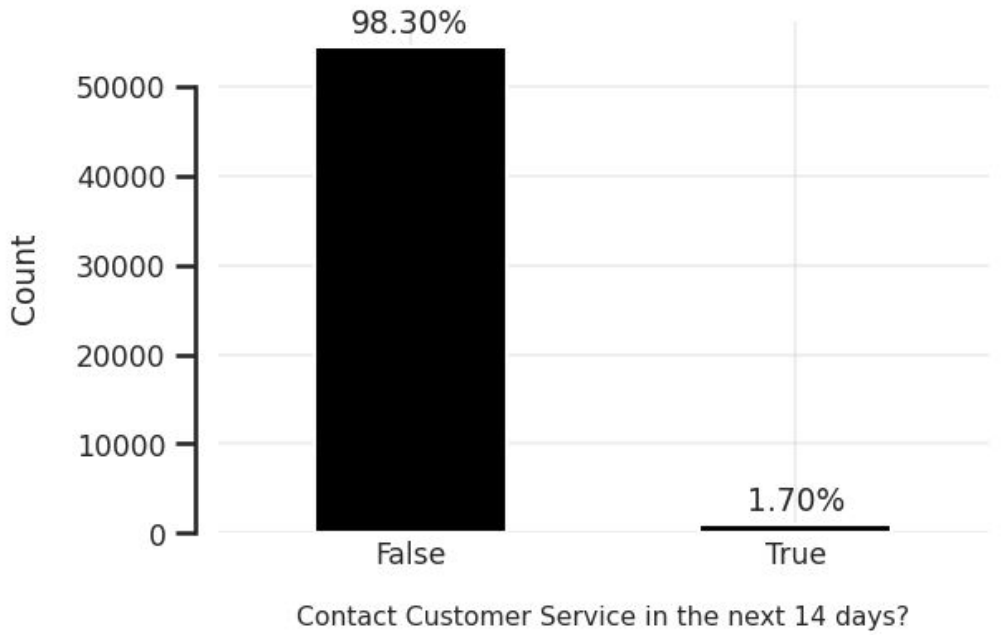
- App: https://crm-app.datargs.com
- FastAPI: https://crm-app.datargs.com

Note: these web services were not shared with anyone. I can delete them after our interview if necessary :)

EDA

Data quality checks

- No missing values (probably they've been filled with -1)
- No duplicated rows
- Constant & quasi-constant features
- Presence of outliers
- Target imbalance



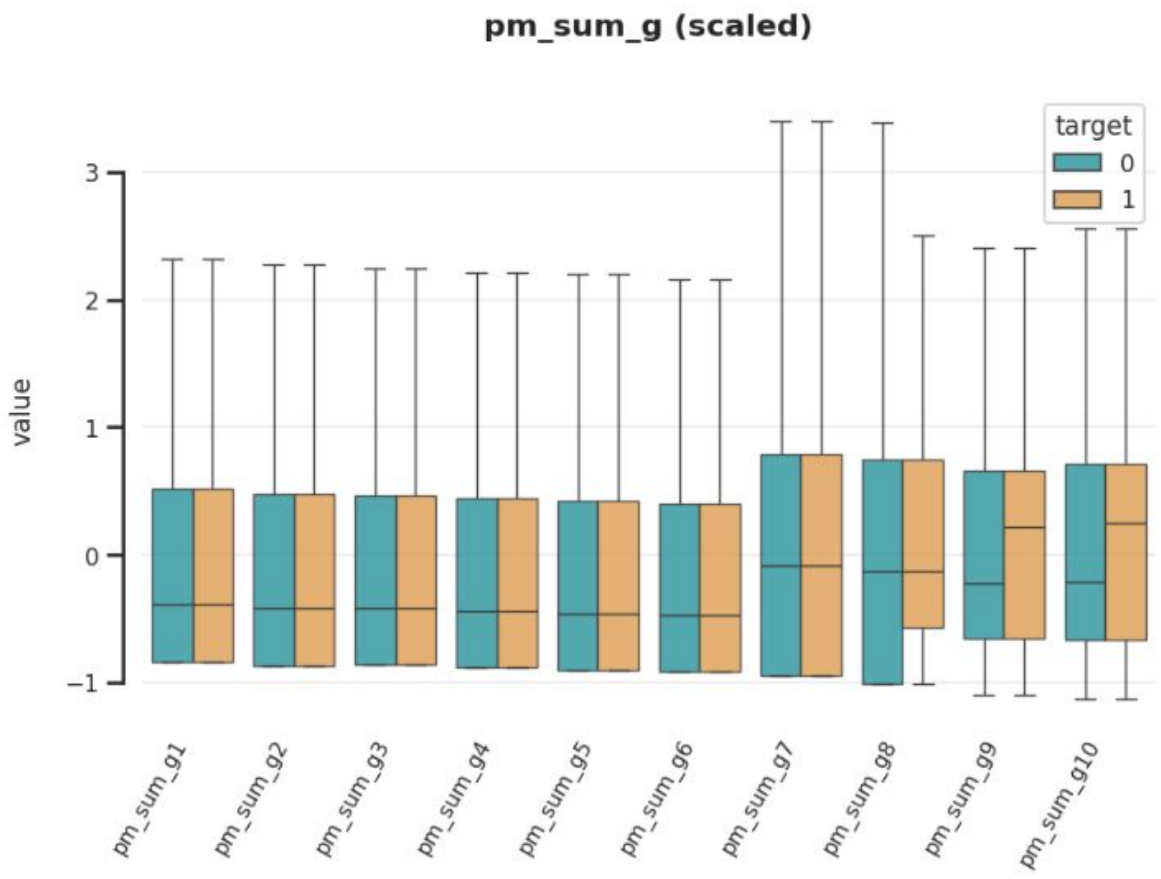
Statistical Analysis

Example of outliers:

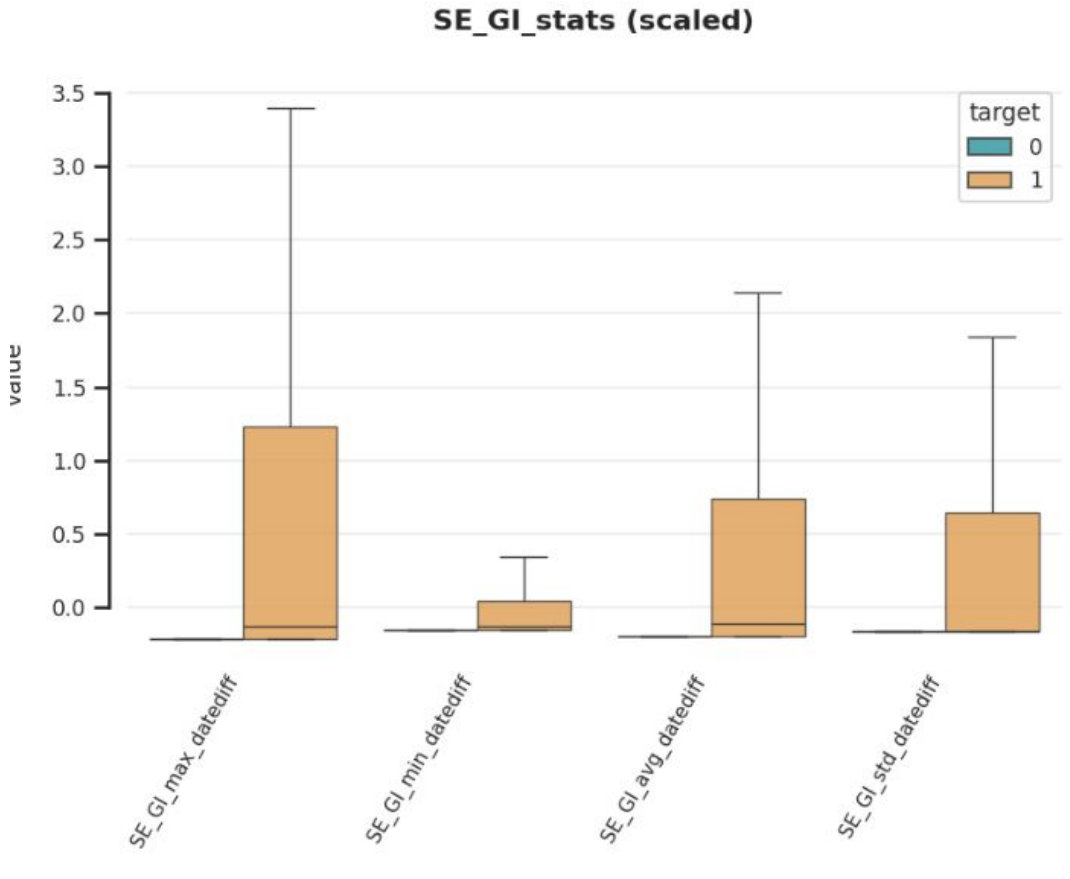
	gw_g8	gw_g7	SE_GI_wrt_days_70days	mar_g3	bon_wrt_succdep_g8	unsucc_dep_g8	SB_to_g8	gw_g2	SB_to_g7	with_sum_g8
count	55415.000000	55415.000000	55415.000000	55415.000000	55415.000000	55415.000000	5.541500e+04	55415.000000	5.541500e+04	55415.000000
mean	-86.992825	-85.059200	0.000018	-0.092597	0.971746	173.537111	4.237183e+02	-91.566777	3.586638e+02	222.618962
std	2582.774584	2532.532325	0.004248	2.330595	32.793466	4083.854676	8.789732e+03	1517.749186	6.627518e+03	2465.312225
min	-163365.400000	-85766.660000	0.000000	-0.999800	0.000000	0.000000	0.000000e+00	-176602.780000	0.000000e+00	0.000000
25%	-103.864700	-100.050000	0.000000	-0.202600	0.000000	0.000000	0.000000e+00	-85.464550	0.000000e+00	0.000000
50%	-14.950000	-11.600000	0.000000	-0.024500	0.000000	0.000000	0.000000e+00	-3.100000	0.000000e+00	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.053100	30.000000	4.826810e+01	0.000000	2.266515e+01	65.000000
99%	1378.881476	1304.765296	0.000000	0.814158	16.044000	2758.542340	6.758736e+03	1199.805400	6.206709e+03	3362.277996
99.5%	2372.264353	2463.224288	0.000000	1.289123	32.545768	4639.725315	1.188462e+04	2235.062937	1.066179e+04	5379.028963
max	478379.799800	513582.087500	1.000000	541.421200	7152.580000	887001.000000	1.853940e+06	142312.570000	1.350032e+06	479756.089000

Statistical Analysis

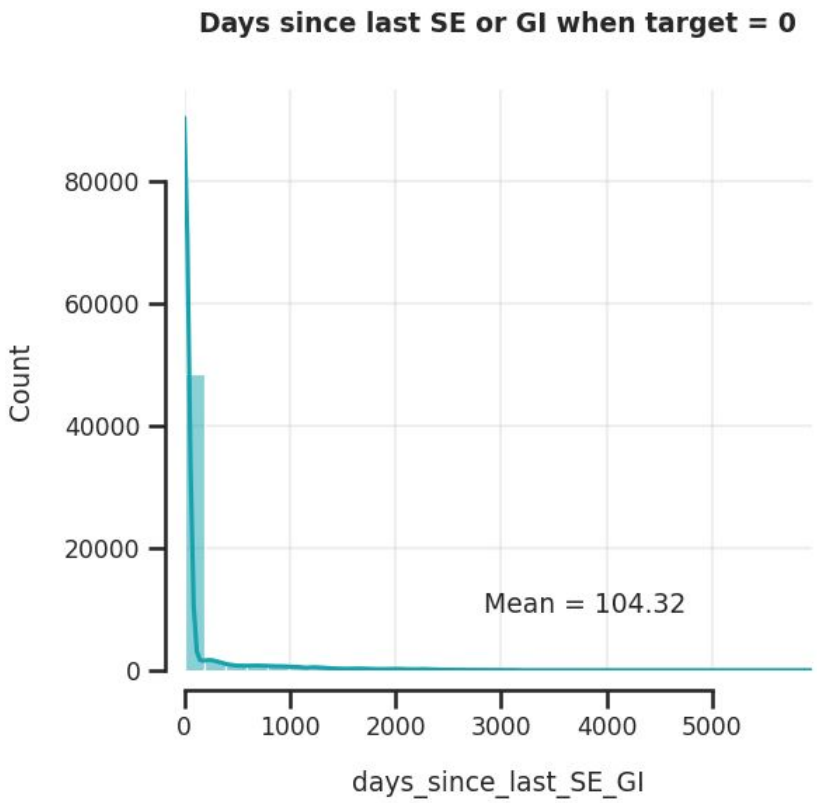
Example of non-informative features

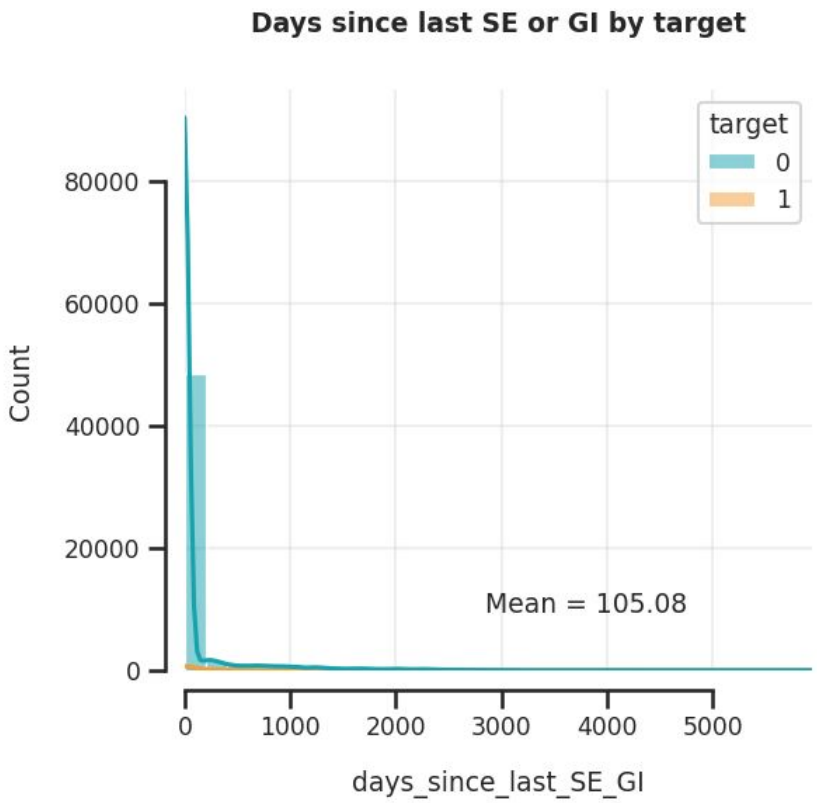


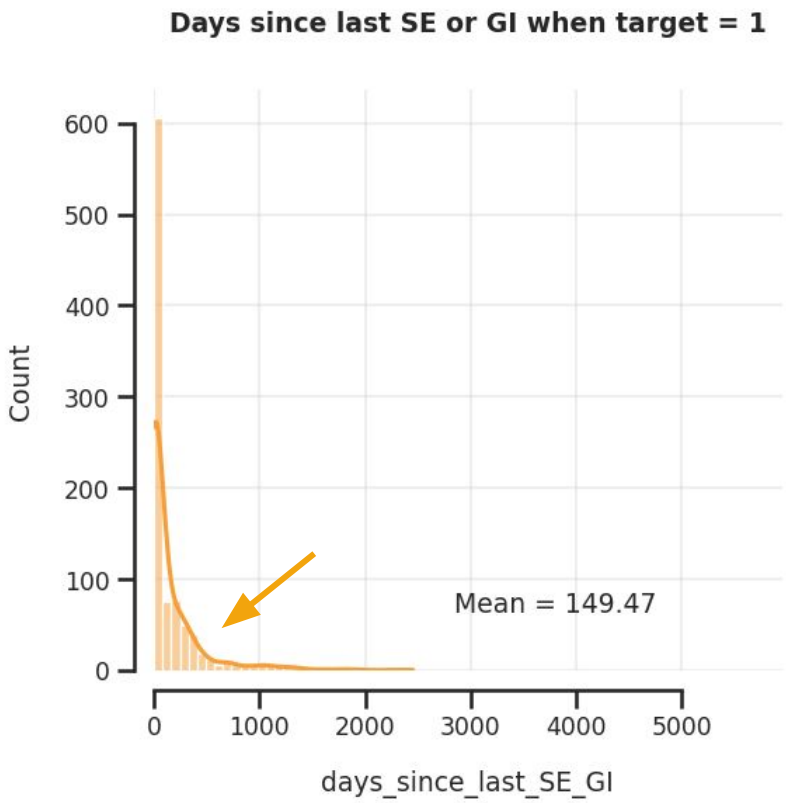
Example of informative features



Statistical Analysis







Example of feature with potential impact to the model

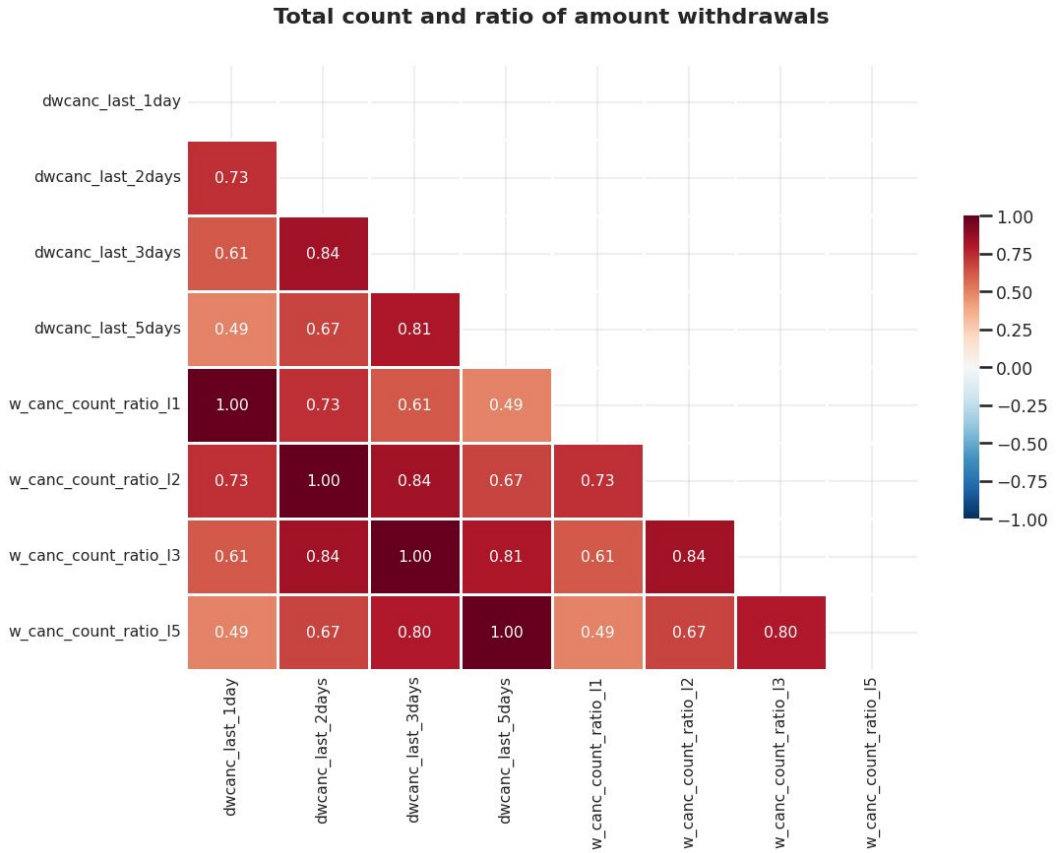
Statistical Analysis

Mann–Whitney U test:

- 198 statistically significant features
- 69 non-statistically significant features

Spearman correlation:

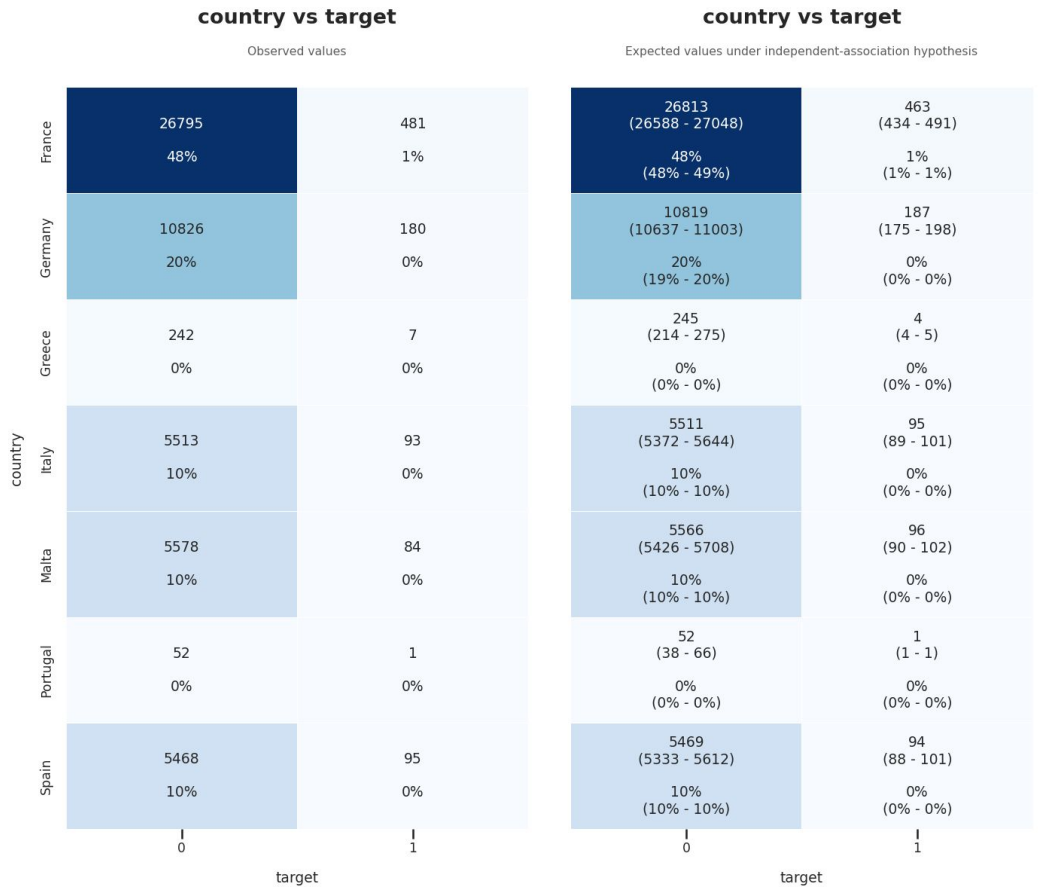
- Many features are highly correlated (multicollinearity)

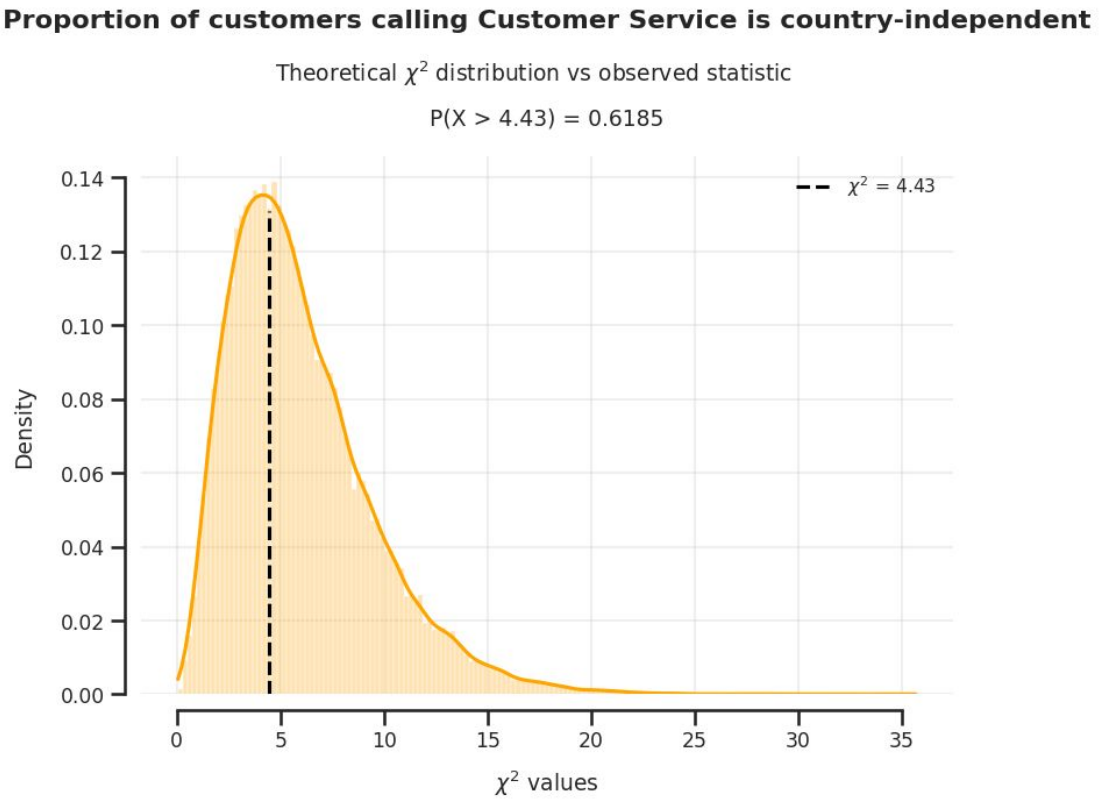


Statistical Analysis

Chi2 test:

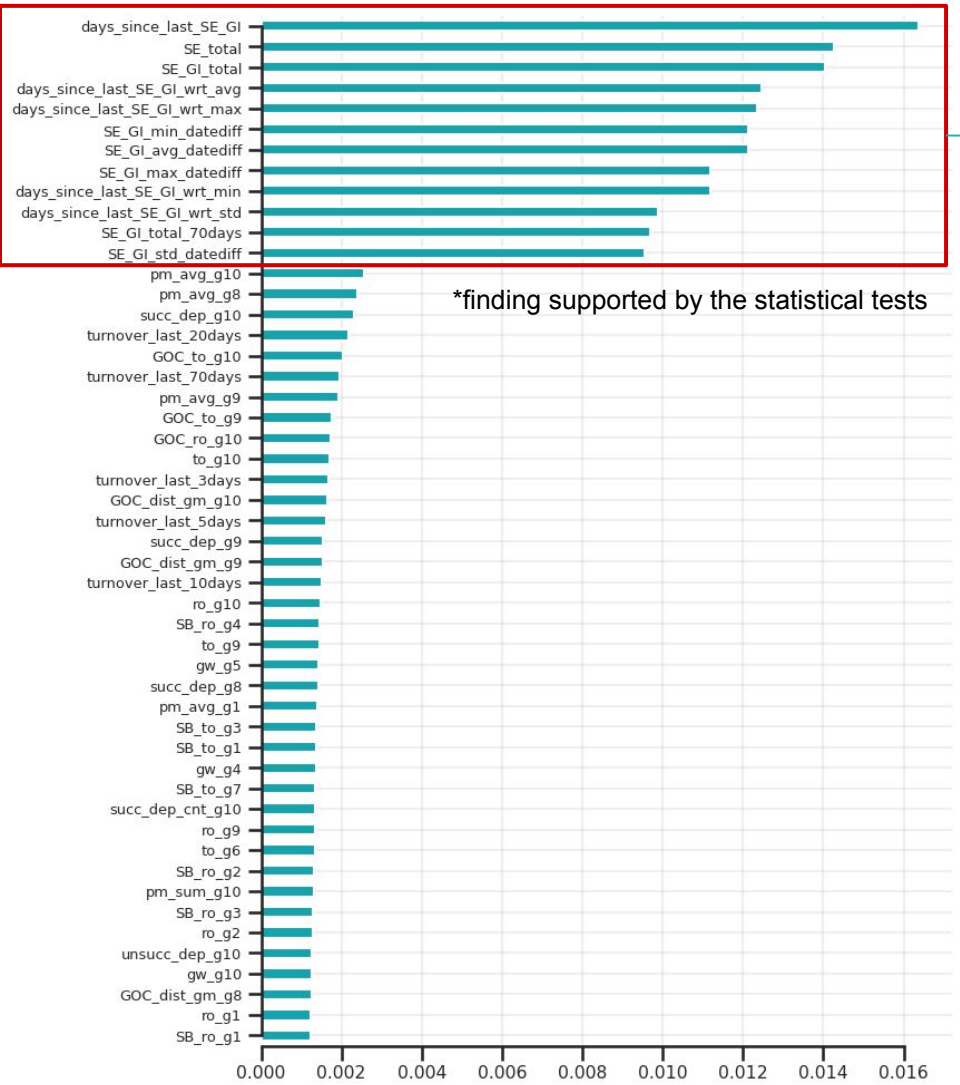
- The country feature **is not** associated with our target





Statistical Analysis

Mutual Information (MI) scores:



*finding supported by the statistical tests

According to the mutual information (MI) scores and statistical tests, features related to Gambling issues and self-exclusion might be important to predict if the the customer will or will not call the customer service.

Feature Selection

- Removal of low-variance (quasi-constant) features (>0.01) → 3+1 features
- Winsorizing extreme outliers within the ML pipeline (99.99th percentile) → 0 features
- Removal of correlated features (keep the ones with the highest variance) → 69 features
- Select top 12 features performing similarly to a the models with all features

Predictive Modeling

Model Selection

Test models with default parameters and all variables results in poor recall or accuracy:

	Model	Accuracy	AUC	Recall	Prec.	F1	FPR	FNR	AUC-PR	TT (Sec)
nb	Naive Bayes	0.1629	0.6843	0.9078	0.0181	0.0355	0.8500	0.0922	0.4637	1.0200
qda	Quadratic Discriminant Analysis	0.2420	0.5458	0.8511	0.0188	0.0367	0.7685	0.1489	0.4362	1.7300
lda	Linear Discriminant Analysis	0.9739	0.7765	0.2624	0.2467	0.2543	0.0138	0.7376	0.2608	1.8600
dt	Decision Tree Classifier	0.9670	0.5755	0.1702	0.1326	0.1491	0.0192	0.8298	0.1584	16.1600
ada	Ada Boost Classifier	0.9829	0.8056	0.0851	0.4800	0.1446	0.0016	0.9149	0.2903	30.3500
lightgbm	Light Gradient Boosting Machine	0.9827	0.8263	0.0851	0.4444	0.1429	0.0018	0.9149	0.2725	2.3200
gbc	Gradient Boosting Classifier	0.9820	0.8449	0.0780	0.3548	0.1279	0.0024	0.9220	0.2242	162.8400
xgboost	Extreme Gradient Boosting	0.9832	0.8065	0.0674	0.5429	0.1199	0.0010	0.9326	0.3130	1.6800
catboost	CatBoost Classifier	0.9831	0.8479	0.0603	0.5152	0.1079	0.0010	0.9397	0.2957	33.1800
ridge	Ridge Classifier	0.9835	0.5281	0.0567	0.6667	0.1046	0.0005	0.9433	0.3697	1.0200
rf	Random Forest Classifier	0.9833	0.7896	0.0142	1.0000	0.0280	0.0000	0.9858	0.5155	7.7300
et	Extra Trees Classifier	0.9830	0.7849	0.0035	0.5000	0.0070	0.0001	0.9965	0.2602	3.4800
lr	Logistic Regression	0.9806	0.5092	0.0000	0.0000	0.0000	0.0025	1.0000	0.0085	17.4100
knn	K Neighbors Classifier	0.9829	0.5203	0.0000	0.0000	0.0000	0.0002	1.0000	0.0085	0.8800
svm	SVM - Linear Kernel	0.9806	0.4988	0.0000	0.0000	0.0000	0.0024	1.0000	0.0085	1.6100
dummy	Dummy Classifier	0.9830	0.5000	0.0000	0.0000	0.0000	0.0000	1.0000	0.5085	0.8200

Model Selection

I wanted to optimize:

- Recall >70%
- Accuracy >70%
- ROC-AUC > 80%

Trade-off = lower precision

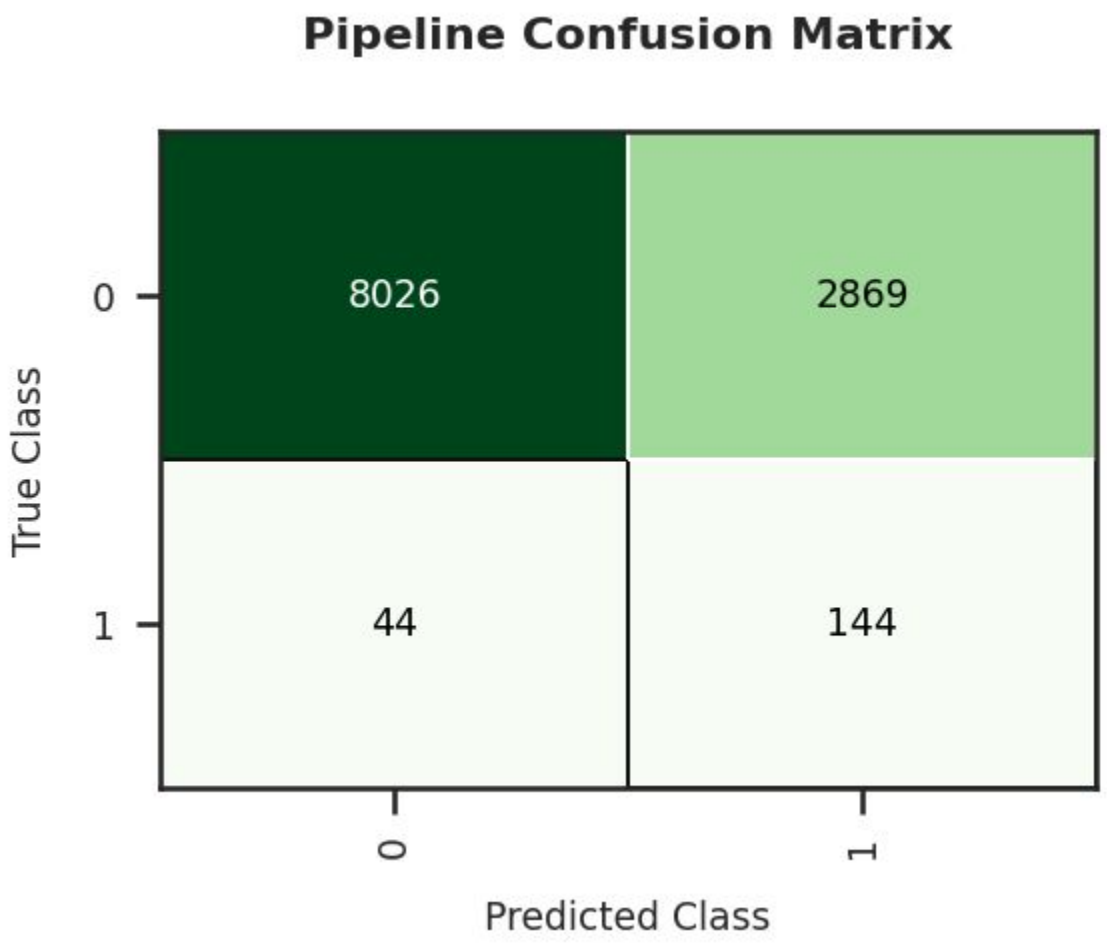
Experiment setup

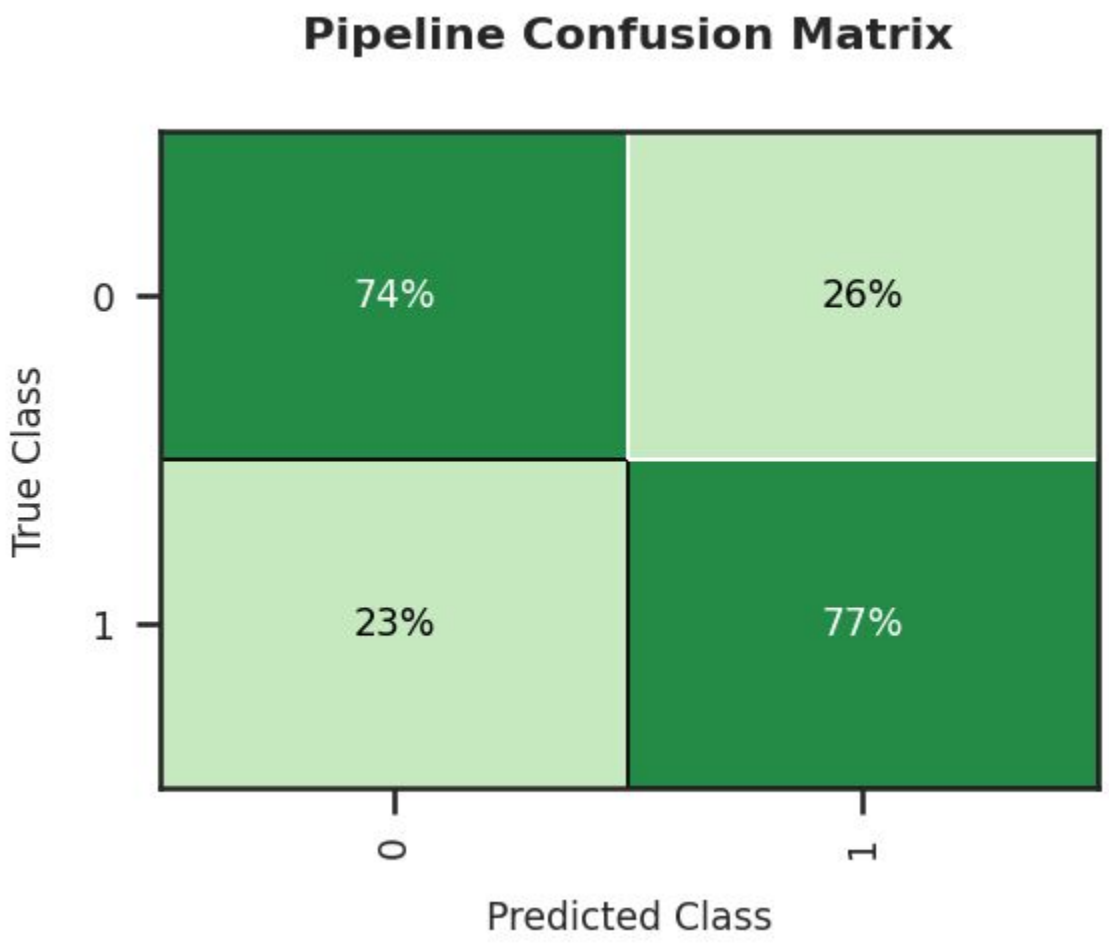
```
# Instantiate experiment
exp = ClassificationExperiment()

# Default experiment setup
exp.setup(
    df, target='target',
    fix_imbalance=True,
    fix_imbalance_method='RandomUnderSampler',
    normalize=True,
    normalize_method='robust',
    remove_multicollinearity=True,
    multicollinearity_threshold=0.9,
    low_variance_threshold=0.01,
    remove_outliers=False,
    feature_selection=False,
    use_gpu=True,
    session_id=42
)

# Set custom metrics
set_custom_metrics(exp)

# Compare available models
best = exp.compare_models(sort='recall', cross_validation=False)
```

Models with basic preprocessing, training set resample, and all features, provided better results:

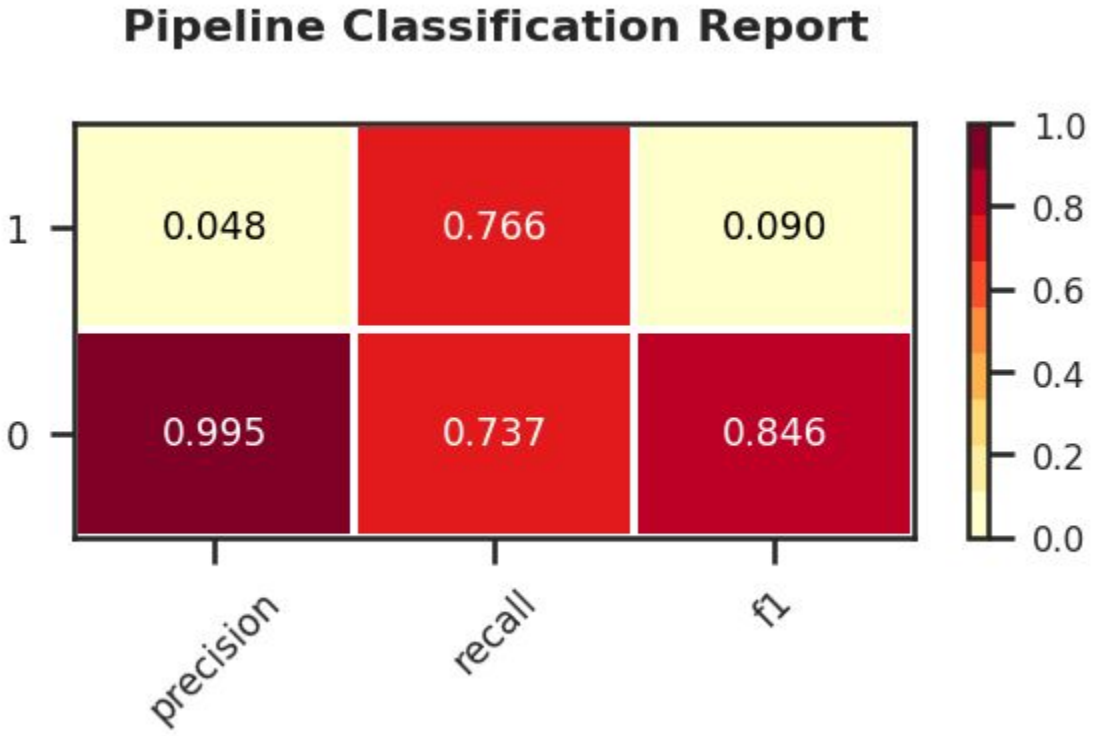
	Model	Accuracy	AUC	Recall	Prec.	F1	FPR	FNR	AUC-PR	TT (Sec)
svm	SVM - Linear Kernel	0.3881	0.5912	0.8014	0.0219	0.0425	0.6190	0.1986	0.4133	8.9200
et	Extra Trees Classifier	0.7711	0.8135	0.7128	0.0512	0.0955	0.2279	0.2872	0.3844	9.0900
catboost	CatBoost Classifier	0.8075	0.8310	0.7128	0.0605	0.1116	0.1908	0.2872	0.3891	31.2400
xgboost	Extreme Gradient Boosting	0.7815	0.8206	0.7092	0.0533	0.0992	0.2173	0.2908	0.3837	9.1900
dt	Decision Tree Classifier	0.6811	0.6915	0.7021	0.0366	0.0695	0.3192	0.2979	0.3719	9.1500
lightgbm	Light Gradient Boosting Machine	0.8002	0.8301	0.6950	0.0571	0.1055	0.1980	0.3050	0.3787	9.6500
gbc	Gradient Boosting Classifier	0.8218	0.8331	0.6915	0.0635	0.1163	0.1760	0.3085	0.3801	13.3700
rf	Random Forest Classifier	0.8225	0.8293	0.6809	0.0629	0.1151	0.1751	0.3191	0.3746	9.2100
ada	Ada Boost Classifier	0.7719	0.7895	0.6702	0.0486	0.0906	0.2263	0.3298	0.3622	9.8300
lr	Logistic Regression	0.7402	0.7391	0.6489	0.0416	0.0781	0.2582	0.3511	0.3482	9.5600
lda	Linear Discriminant Analysis	0.7428	0.7029	0.5816	0.0379	0.0712	0.2544	0.4184	0.3133	8.9400
ridge	Ridge Classifier	0.7444	0.6626	0.5780	0.0380	0.0712	0.2528	0.4220	0.3116	9.0100
qda	Quadratic Discriminant Analysis	0.7183	0.6693	0.5390	0.0323	0.0609	0.2787	0.4610	0.2896	8.9600
knn	K Neighbors Classifier	0.6592	0.6197	0.5106	0.0254	0.0484	0.3382	0.4894	0.2722	9.0700
nb	Naive Bayes	0.8346	0.6823	0.3794	0.0399	0.0722	0.1576	0.6206	0.2149	8.9300
dummy	Dummy Classifier	0.9830	0.5000	0.0000	0.0000	0.0000	0.0000	1.0000	0.5085	8.9000

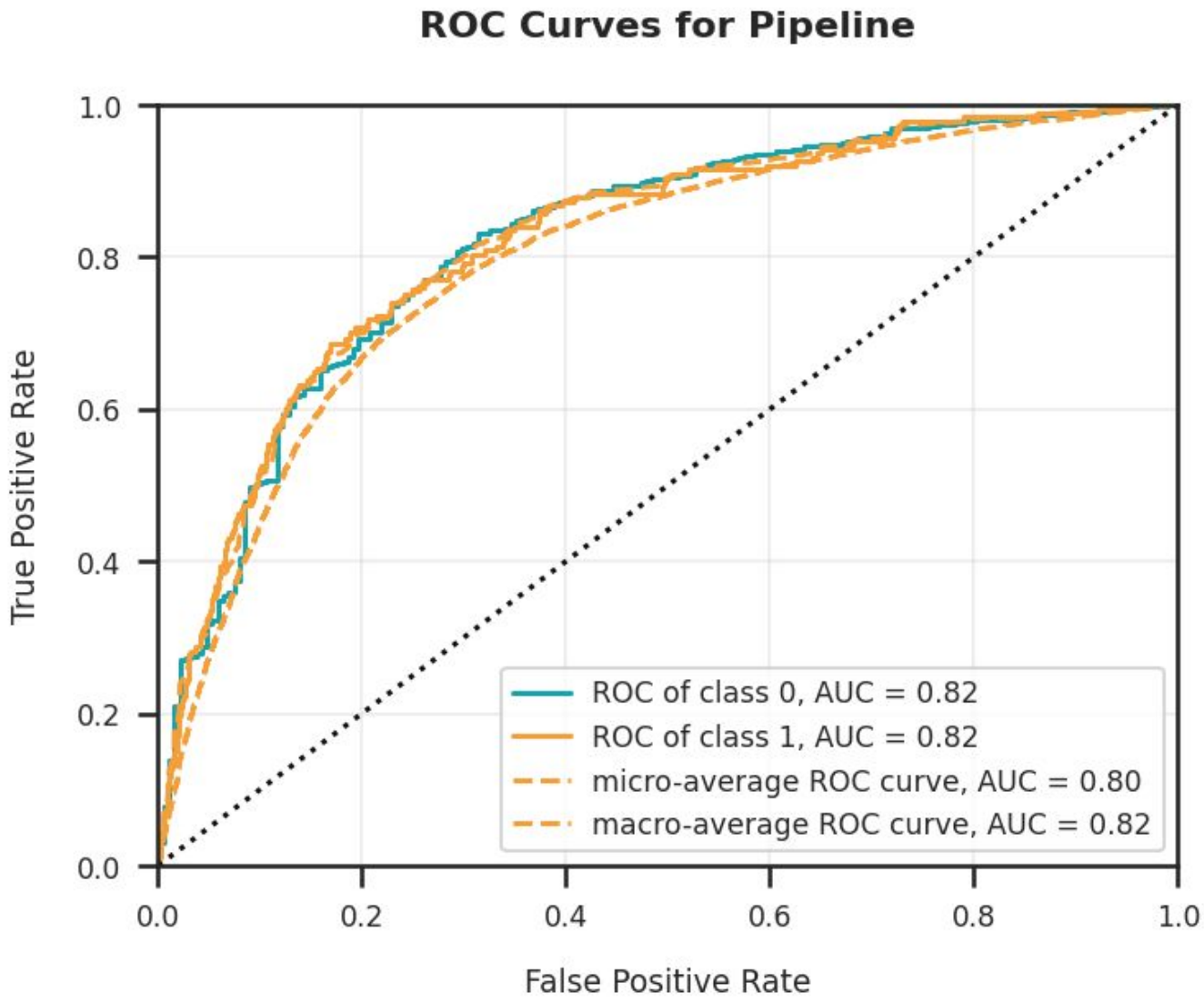
Model evaluation



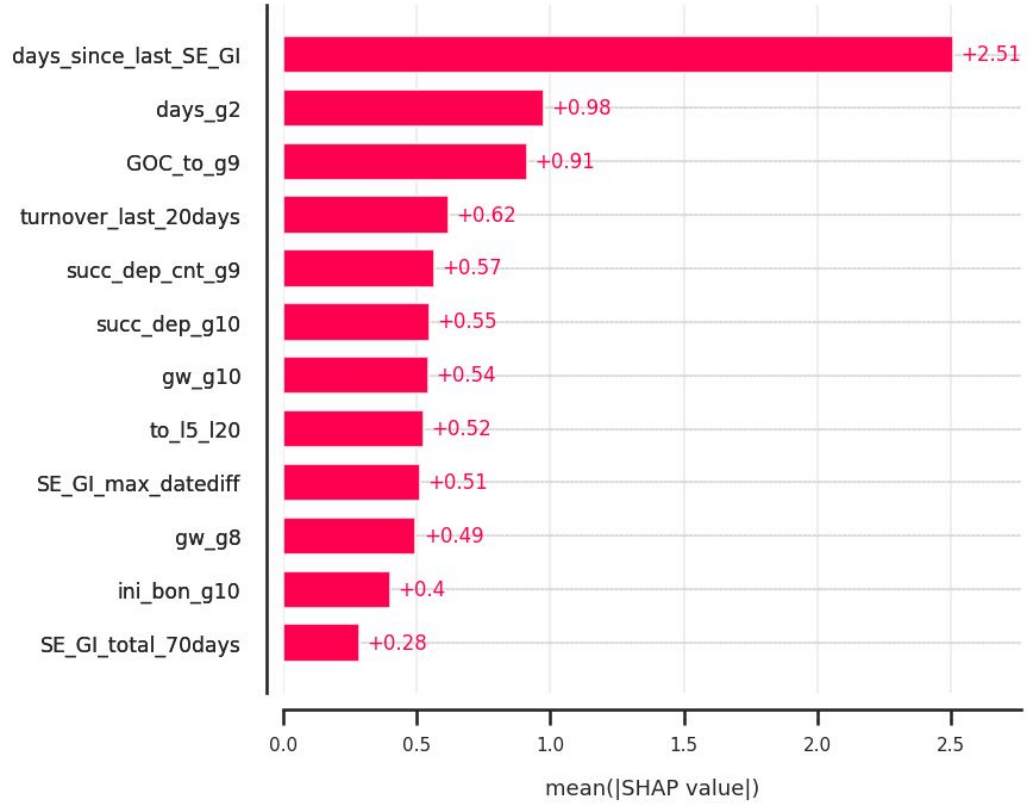


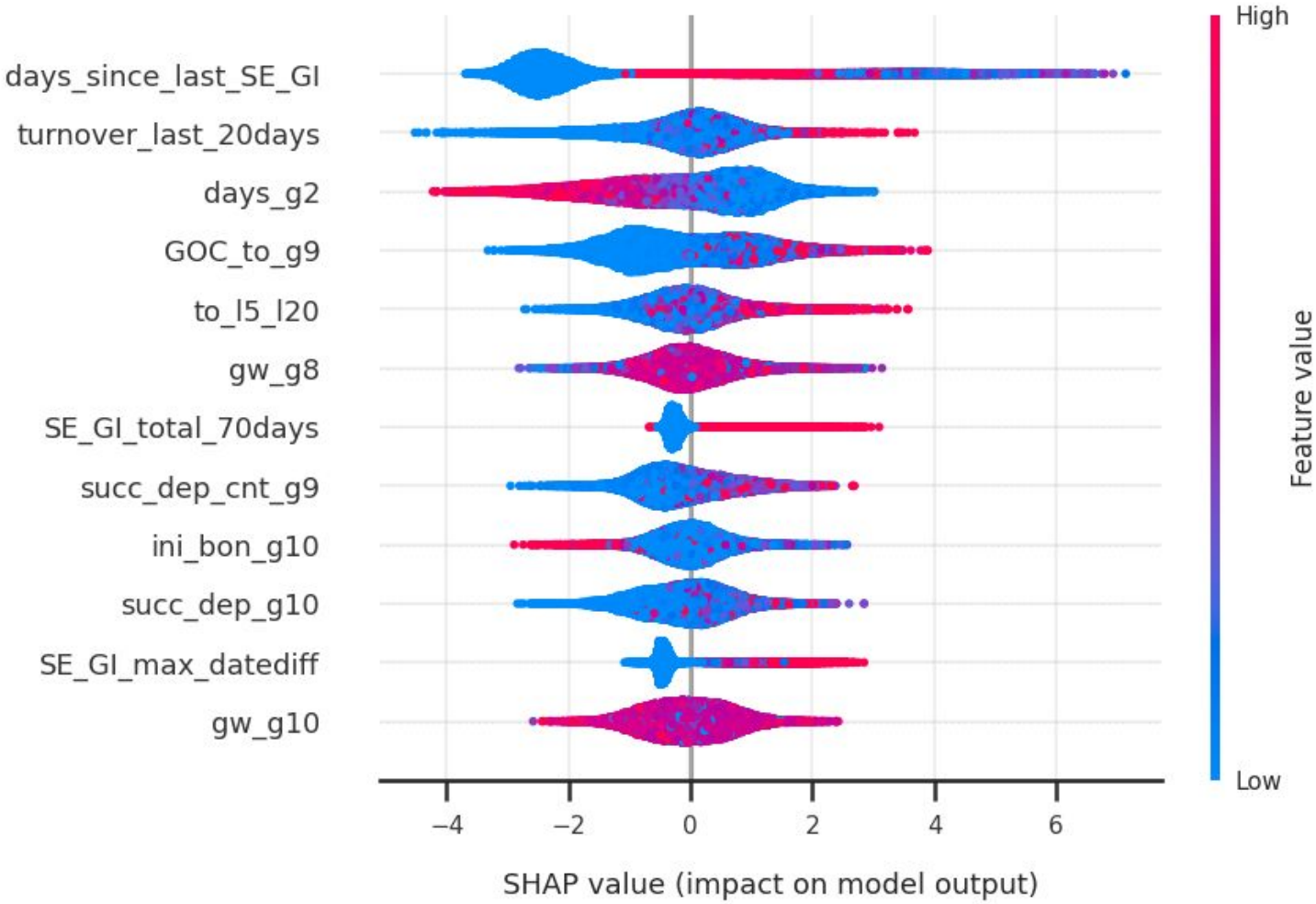
Model evaluation



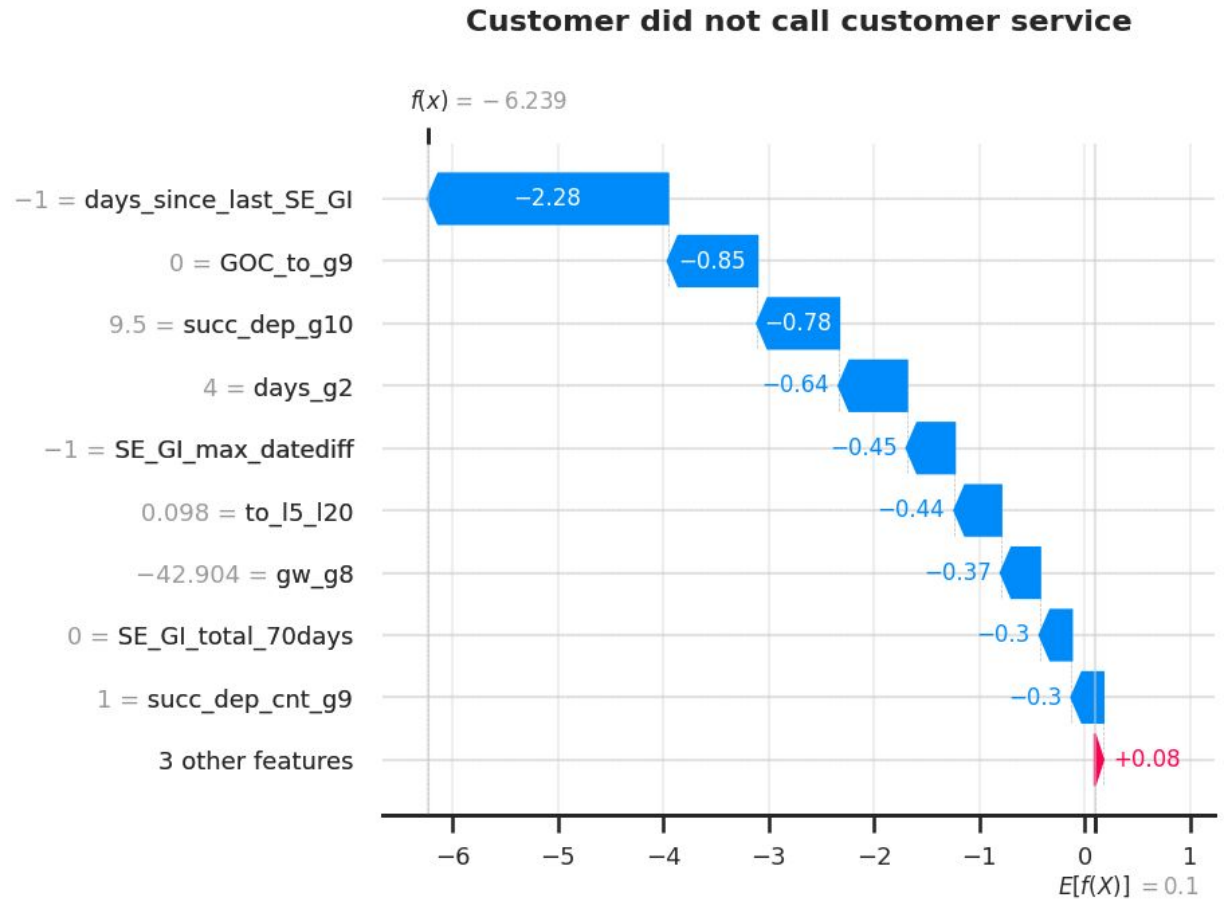


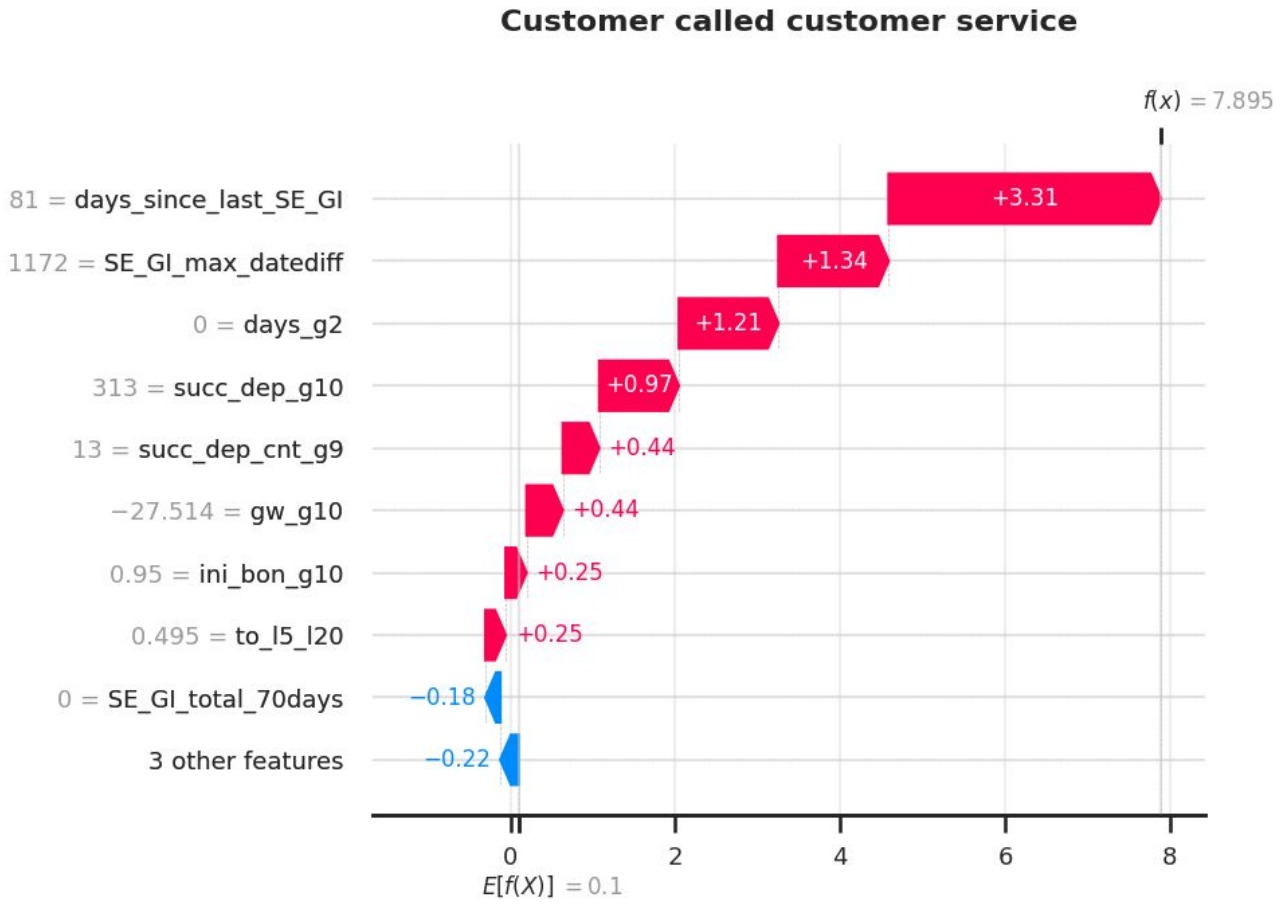
Model Interpretation





Model Interpretation



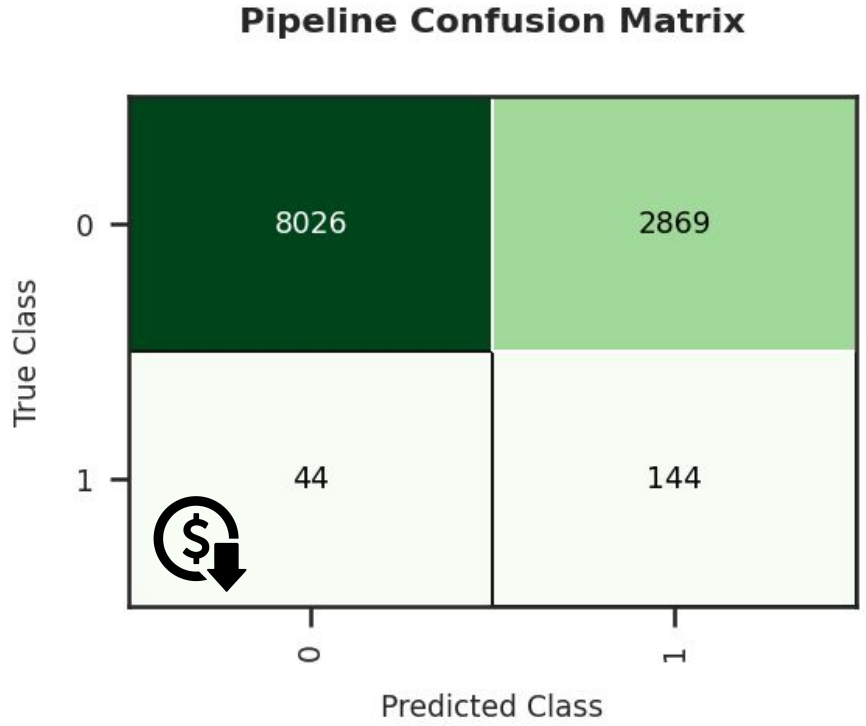


Business alignment

Will this model be used in production?

It depends!

→ How much do we earn by contacting a customer?
→ What's the intervention action cost?
→ What about resources allocation?



Cost?

Earnings?

↑ CLV
↓ Churn

Possible improvements:

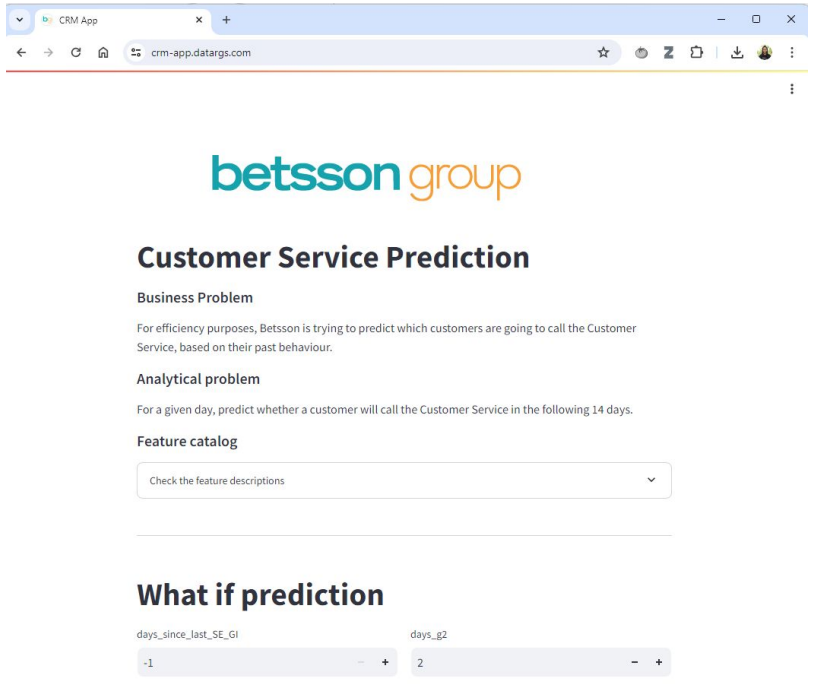
→ Brainstorming and collection of meaningful features
→ Extensive hyperparameter tuning on new models
→ Smarter feature selection using forward/backward selection

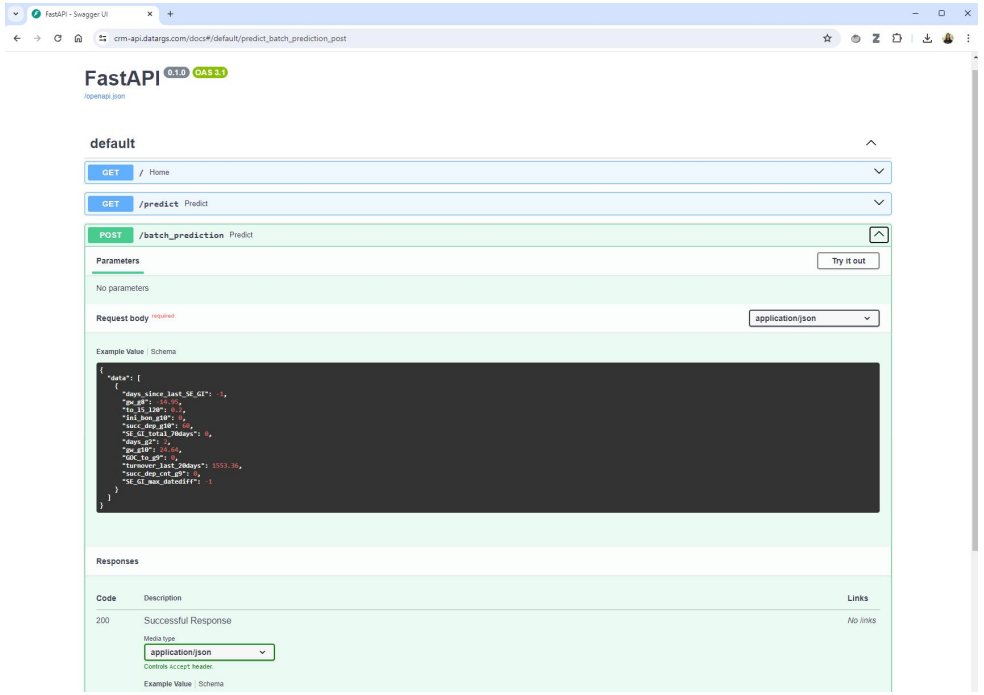
Note: Perhaps the customers who didn't contact Customer Service,
who have features similar to those who contacted them, would benefit from a contact as well.

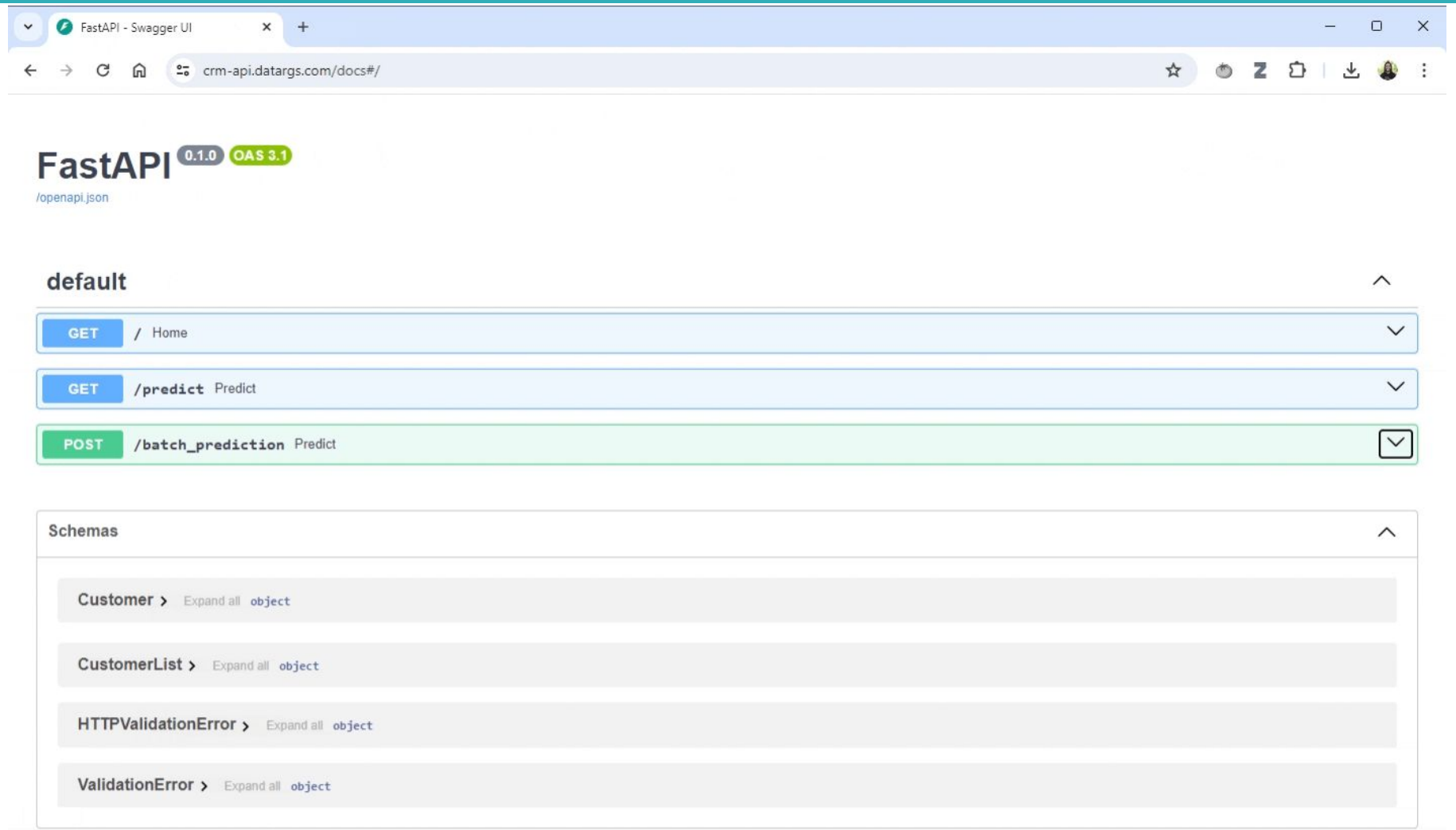
Model Deployment

Model Deployment

- API on Oracle Cloud with a custom domain: crm-api.datargs.com
- Streamlit App on Oracle Cloud with a custom domain: crm-api.datargs.com






FastAPI - Swagger UI
crm-api.datargs.com/docs#/
FastAPI
0.1.0
OAS 3.1
/openapi.json
default
GET / Home
GET /predict Predict
POST /batch_prediction Predict
Schemas
Customer Expand all object
CustomerList Expand all object
HTTPValidationError Expand all object
ValidationError Expand all object

Thank you!