

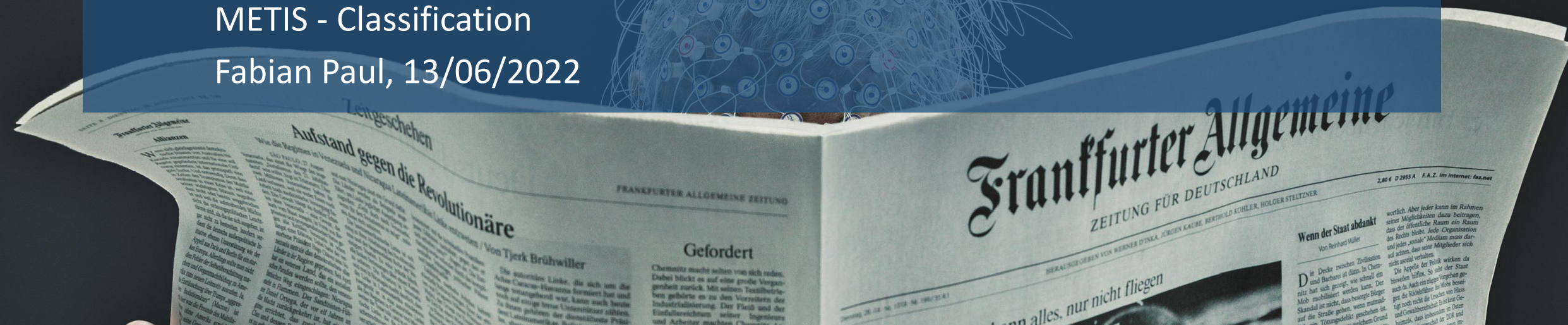
Dahinter steckt
immer ein kluger Kopf.

Predicting Conversions from Print Newspaper Subscription Sales

Analysis for a German publisher (Frankfurter Allgemeine Zeitung)

METIS - Classification

Fabian Paul, 13/06/2022



Introduction

Business Problem

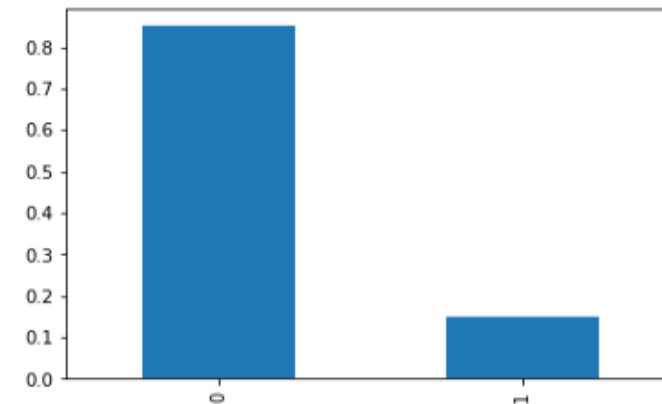


- Print subscriptions most important revenue source
- Converted Subs = Regular Paid Subscriptions with ≥ 90 days duration
- Prediction model crucial for:
 - ... identifying features that drive conversions
 - ... target right customers with “care actions”

Objective

- Which order, customer and product features are significantly correlated to conversions?
- Is it possible to predict conversions instantaneously when an order is received?

```
0    0.850173
1    0.149827
Name: conversion, dtype: float64
```



Methodology

Order Data



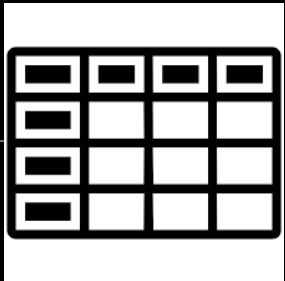
13,015 Transactions Q3/2021

- Orders
- Products
- Customers

Feature Engineering

- Convert subscription data (SAP) into usable format
- Create bins of broader categories
- Generate target variable for each subscription
- Generate features on past customer relationships
- Convert categories to dummies

liefende	12269
gultig_bis	11886
erfdat_kun	2354
aart	13015
posart	13015
bezgrd	13015
preisgruppe	5207
bezgrd_lfzt	13015
bezgrd_option	13015
faktura_period	13015
werbeart	13015
abgangs_typ	13015
lieferart	13015
zahlweg	13015
sachpramie	13015
rg	5210
we	13015
we_anrede	13015
we_optin_email	13015
we_optin_tel	13015
we_optin_brief	13015
amount	13015
we_title_cat	13015
age_cat	5930
cust_type	13015
marketing_channel	13015
rg_we	13015
state	13015
conversion	13015
offer_id	13015
offer_rebate	9479
days_since_last_order	7265
days_since_first_order	13015
no_orders_twohalfyears	13015
no_orders_oneyr	13015
no_orders_halfyr	13015
active_subs_atorder	13015
active_digsups_atorder	13015
active_sundayprint_atorder	13015
days_since_last_enddate	13015
days_since_last_churndate	13015
diff_start_order	13015
order_day	13015
type	13015

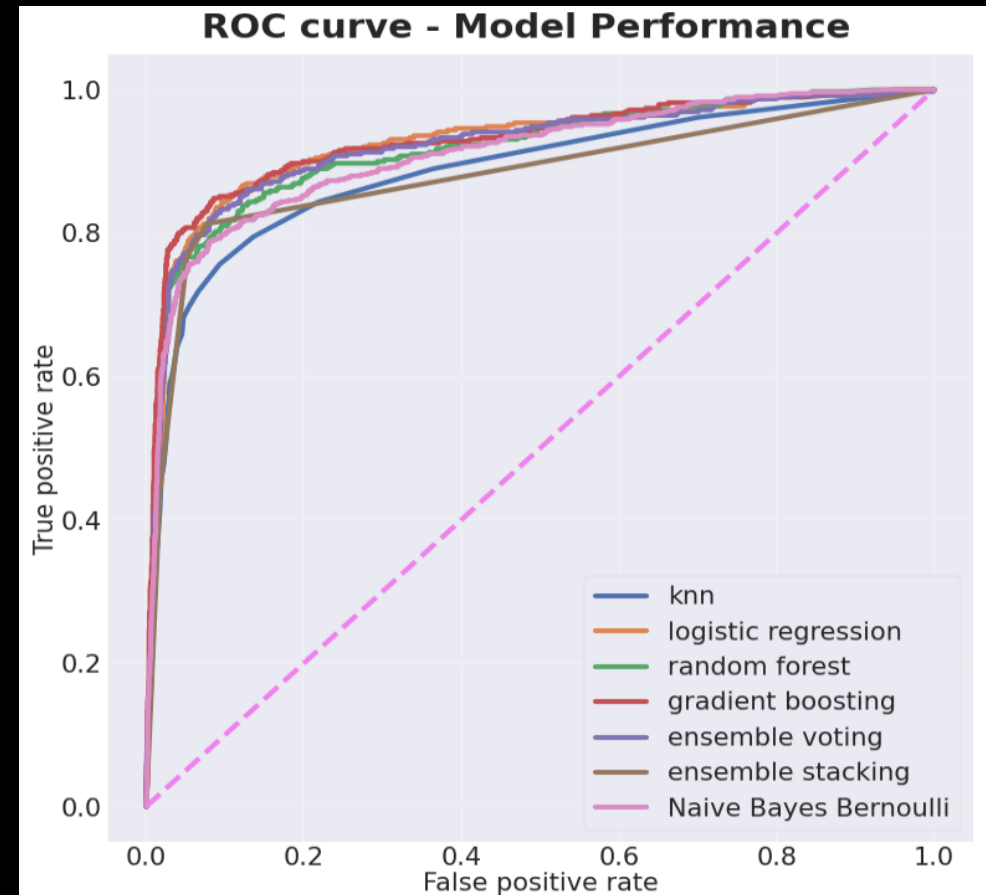


Results

Model Evaluation

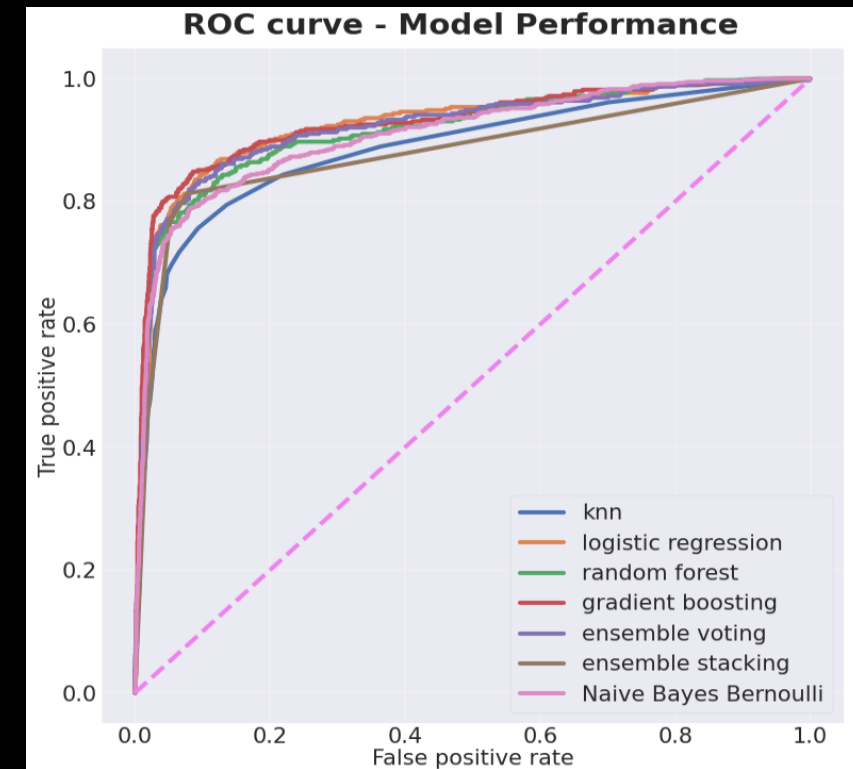
Precision Scores:

```
Gradient Boosting = 0.8385269121813032
Logistic Regression = 0.6509240246406571
Ensemble Voting = 0.7730870712401056
Random Forest = 0.6810933940774487
Naive Bayes Bernoulli = 0.738831615120275
KNN = 0.8104265402843602
Ensemble Stacked = 0.7228915662650602
```



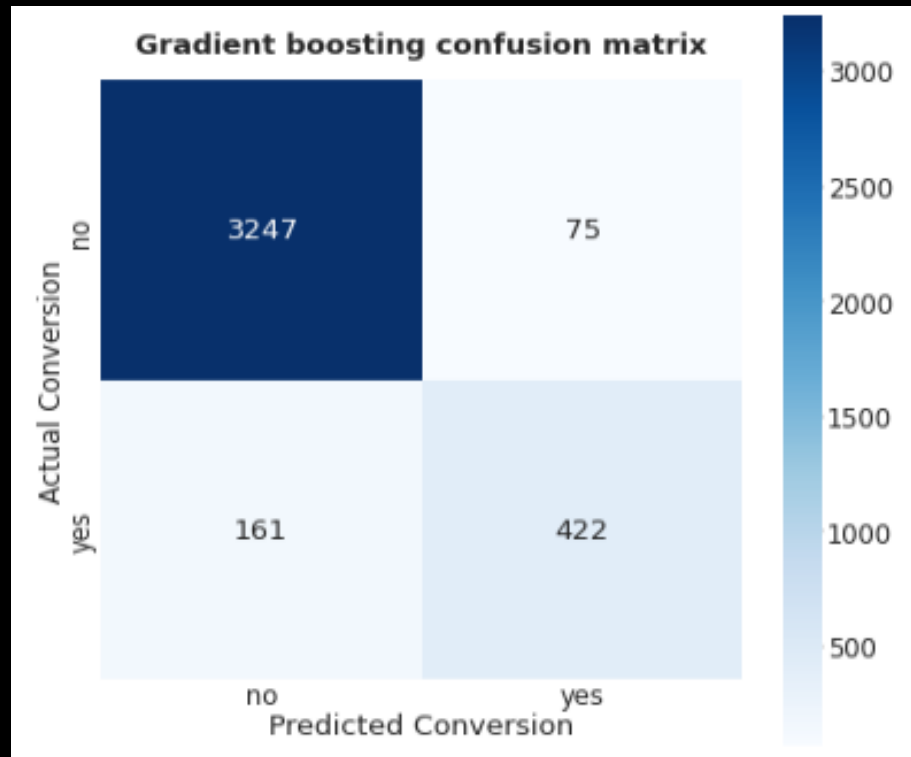
Results

	Precision	F1 Score	Recall	ROC AUC	Logloss
KNN	0.81	0.57	0.44	0.90	0.43
Logistic Regression	0.65	0.72	0.81	0.93	0.30
Random Forest	0.68	0.72	0.77	0.92	0.29
Gradient Boosting	0.84	0.80	0.76	0.94	0.19
Naive Bayes	0.74	0.74	0.74	0.91	0.33
Ensemble Stacking	0.72	0.75	0.77	0.88	0.23
Ensemble Voting	0.77	0.76	0.75	0.93	0.25

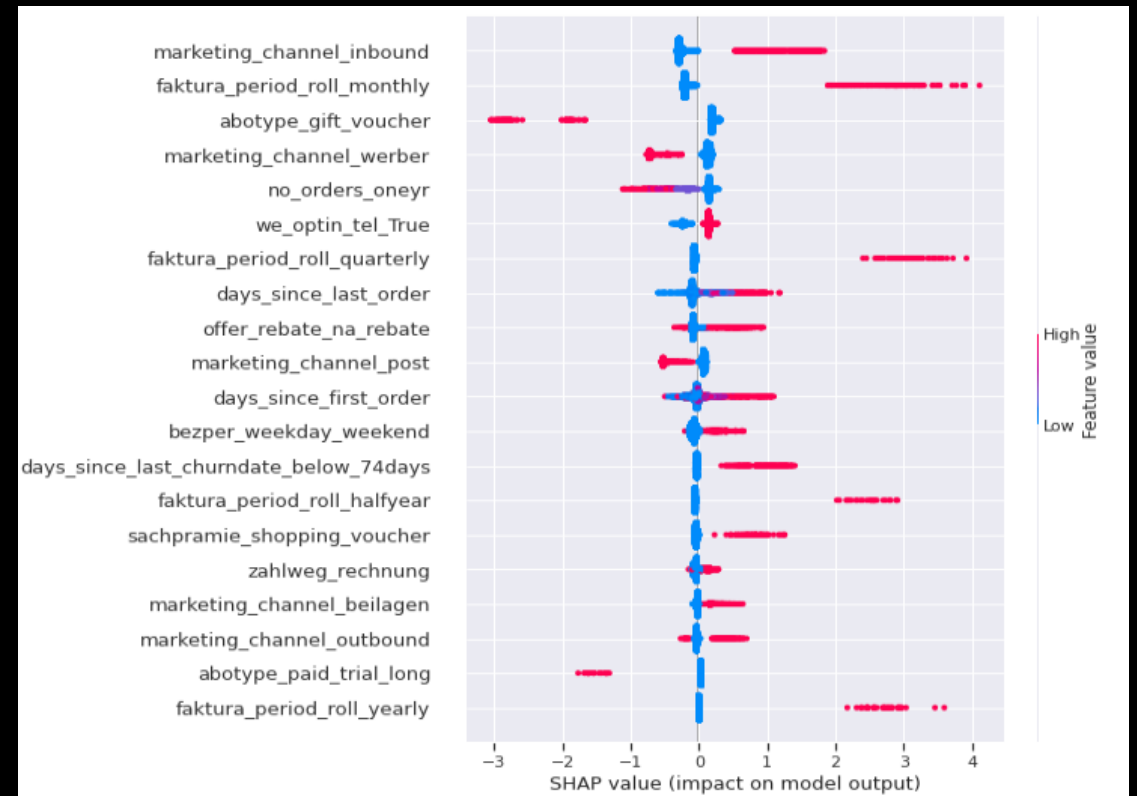


Results

Confusion Matrix



Feature Importance



Conclusions

Takeaways

- Order Features:
 - Marketing channel, payment period, shopping voucher
- Customer features:
 - No. of orders in last year, days since first & last order, optin-approval
- It is possible to predict conversions right after a subscription sale with high precision

Limitations

- Only Weekday Print Subscriptions
- Prediction only at point of order (not afterwards)
- No information on digital product usage
- No information on customer service data
- Socio-demographic data not available for all records

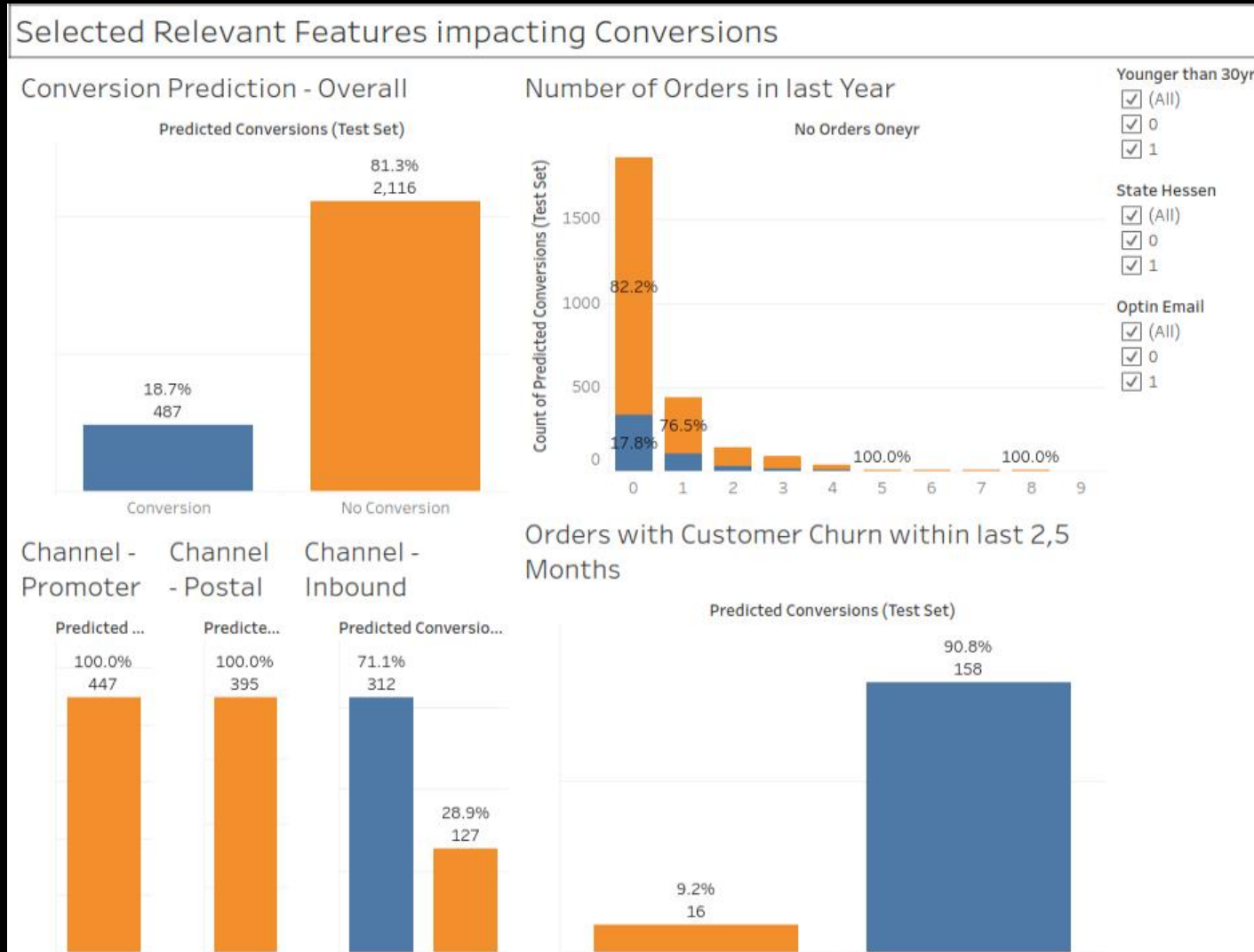
Future Work

- ① → Train model on more products besides weekday print
- ② → Include digital product usage and customer service data
- ③ → Fit model each day to account for different subscription durations at time of training
- ④ → Interactive Web-Interface
- ⑤ → Exclusion of not meaningful features, automated model selection & code efficiency

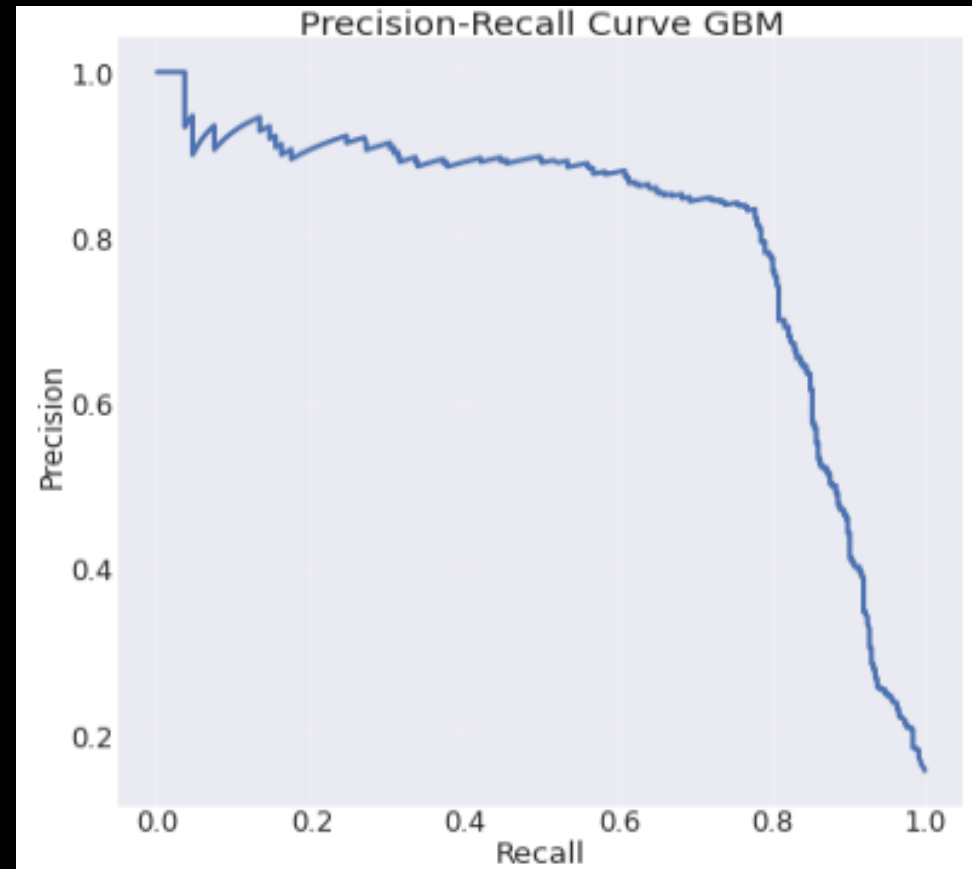
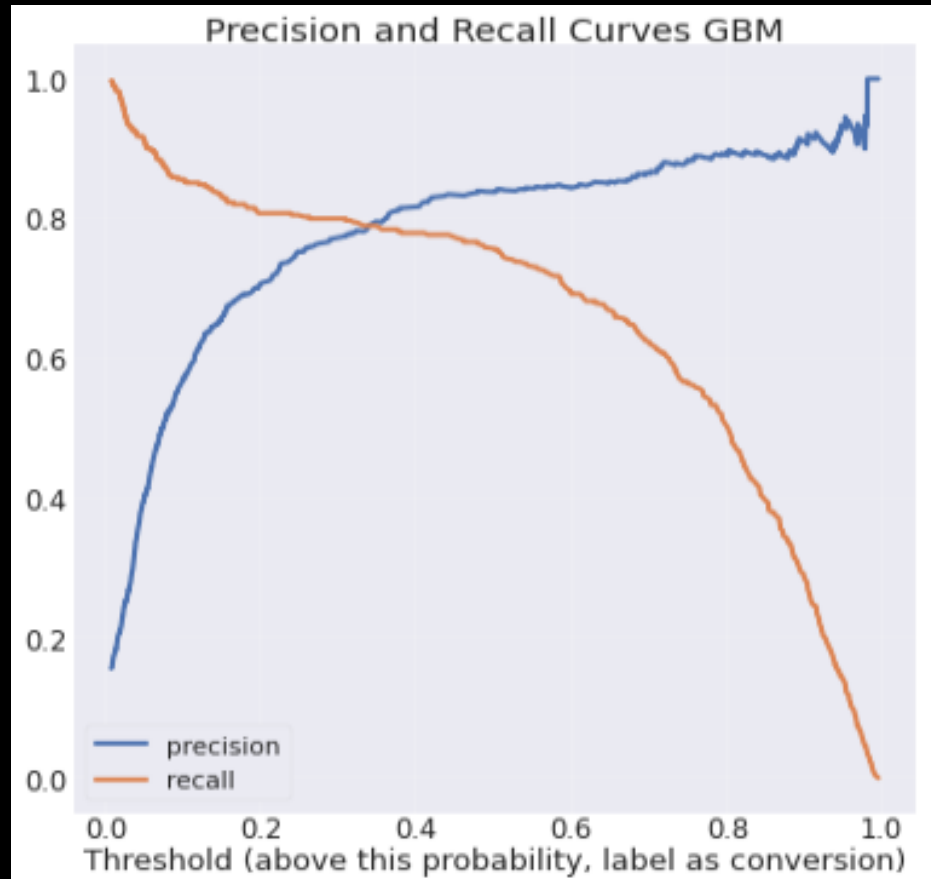


Thank you for your attention!

Appendix I: Selected Features (Tableau)



Appendix II: Precision and Recall Curves Gradient Boosting



Appendix III: Feature Coefficients

Logistic Regression

	Feature	Coefficients
0	faktura_period_roll_monthly	2.588469
1	faktura_period_roll_quarterly	2.492067
2	faktura_period_roll_yearly	2.108892
3	faktura_period_roll_halfyear	2.023117
4	marketing_channel_inbound	1.699640
...
76	no_orders_oneyr	-0.601616
77	marketing_channel_post	-0.677757
78	marketing_channel_werber	-0.948955
79	abotype_paid_trial_long	-1.279328
80	abotype_gift_voucher	-3.131272

81 rows × 2 columns

Appendix IV: Correlation Heatmap

