# A Simple yet Efficient Method for a Credit Card Upselling Prediction

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Solution of ECML/PKDD 2016 Discovery Challenge Task 2 "Upselling prediction", team "Peter"



# Approach

#### User information

	AGE_CAT	LOC_CAT	INC_CAT	GEN	LOC_GEO_X	LOC_GEO_Y
USER_ID						
91498	b	С	b	1	602700	49100

#### User transactions

	USER_ID	POI_ID	CHANNEL	DATE	TIME_CAT	LOC_CAT	MC_CAT	CARD_CAT	AMT_CAT	GEO_X	GEO_Y
0	91498	28052	p	2014-01-01	a	b	b	d	b	605119.0	58997.8
157469	91498	26943	р	2014-01-08	ь	С	e	d	a	602312.0	49289.0
2009139	91498	26943	p	2014-04-02	b	С	e	d	ь	602312.0	49289.0
2934556	91498	26943	р	2014-05-14	a	С	e	d	b	602312.0	49289.0
3356486	91498	28052	p	2014-06-03	b	b	b	d	b	605119.0	58997.8
3410068	91498	14978	р	2014-06-05	b	b	е	d	С	603951.0	58409.1
4882432	91498	3419	р	2014-08-11	b	ь	b	d	b	587174.0	77853.4
5018046	91498	28433	р	2014-08-16	b	b	a	d	С	590234.0	57492.4
5278427	91498	28052	р	2014-08-29	ь	ь	b	d	С	605119.0	58997.8
5638258	91498	10913	p	2014-09-13	a	b	a	d	b	591372.0	57098.2

#### Feature vector:





- Cards & Wealth (8)
- Activeness (8)
- Event counters (77)
- Geo (28)



Predict target (credit card in the future) using **XGBoost** 

# Features: User information

#### **Personal features**

- Gender
- Age category
- Location category
- Income category

One-hot & label encoded

#### **Card & Wealth features**

	C201401	C201402	C201403	C201404	C201405	C201406
USER_ID						
328787	0	1	1	0	0	0

- Number of months labeled as "1"
- Number of label changes "0" -> "1" and vice versa
- Last month labeled "1"

# Features: Event counters

	USER_ID	POI_ID	CHANNEL	DATE	TIME_CAT	LOC_CAT	MC_CAT	CARD_CAT	AMT_CAT
0	91498	28052	р	2014-01-01	a	b	b	d	b
157469	91498	26943	р	2014-01-08	b	С	е	d	а
2009139	91498	26943	р	2014-04-02	b	С	е	d	b
2934556	91498	26943	р	2014-05-14	a	С	е	d	b
3356486	91498	28052	р	2014-06-03	b	b	р	d	b
3410068	91498	14978	р	2014-06-05	b	b	е	d	С

#### Two features for each category value:

- Number of events integer
- Ratio of events with particular value in all user events rational in [0, 1]

#### **Categorical features in user transactions:**

- 1. Type of activity (point of sale, webshop, branch)
- 2. Rounded time period (morning, daytime, evening)
- Location type (capital, city, village)
- 4. Marker category of payment (7 anonymous categories)
- 5. Type of card (credit, debit)
- 6. Amount of money (low, medium, high)

### Features: Activeness

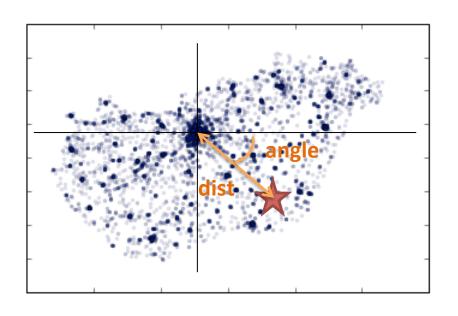
Mon	Tue	Wed	Fri	Sat	Sun	
1	2	3	4	5	6	7
8	9	10	11	12	13	14
15	16	17	18	19	20	21
22	23	24	25	26	27	28
29	30					

**Active** = at least one transaction during the period (days and weeks)

#### Features:

- Number of active / inactive periods
- Ratio of active periods

# Features: Geo location



#### **Geo-features of one transaction:**

- coordinates
- distance to the center (Budapest)
- horizontal angle of location wrt the center

#### **Aggregation of transaction geo-features:**

- min, max
- mean, std
- percentiles (20%, 50%, 80%)

# Tuning learning parameters

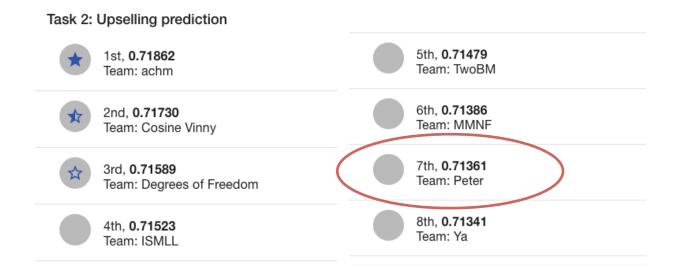
- Validation: 10x stratified shuffle split on learning (90%) and validation (10%)
- Parameters to tune
  - tree depth
  - learning rate
  - number of trees in ensemble
  - scheme of filling the missing values
  - number of unimportant features to exclude
- Decision
  - Marginal improvement in validation score (about 0.005 with big variance)
  - Biased validation scheme (because of year-to-year changes)
  - Final submission: XGBoost model with default learning parameters (Occam's Razor principle)
    - 100 trees, max depth = 3, learning rate = 0.1

# Feature evaluation

Cross-validation AUC score: **0.7213** (stratified shuffle train/test split)

Feature group	AUC change after removing feature group	AUC only features from the group
Personal	-0.0322	0.6615
Cards & Wealth	-0.0137	0.5653
Event counters	-0.0019	0.6738
Activeness	-0.0012	0.6419
Geo location	-0.0004	0.6318

# That's it!



#### **Solution source code:**

https://github.com/romovpa/ecmlpkdd2016-otp-bank-upselling