



# Customer Intelligence in der Praxis

IT-Logix AG  
Sotiris Dimopoulos, PhD

Zürich, 11. September 2018



# Data Science & AI : Possibilities?

**Understand**

**Improve**

**Predict**

MARKET BASKET ANALYSIS

of people who purchased items A and B also purchased item C

AUTOMATION

PLANNING AND CONTROL

Sales data ARMA(1,0)

PRODUCTS CUSTOMERS

MULTI-SENSORY SURVEILLANCE METHOD

SCHEDULED OIL ANALYSIS

FAILURE INCEPTION

FUNCTIONAL FAILURE (consequence stop)

Multi-modal operational defects problem with Unidentified oil sample sent to lab for diagnosis

## Outlook

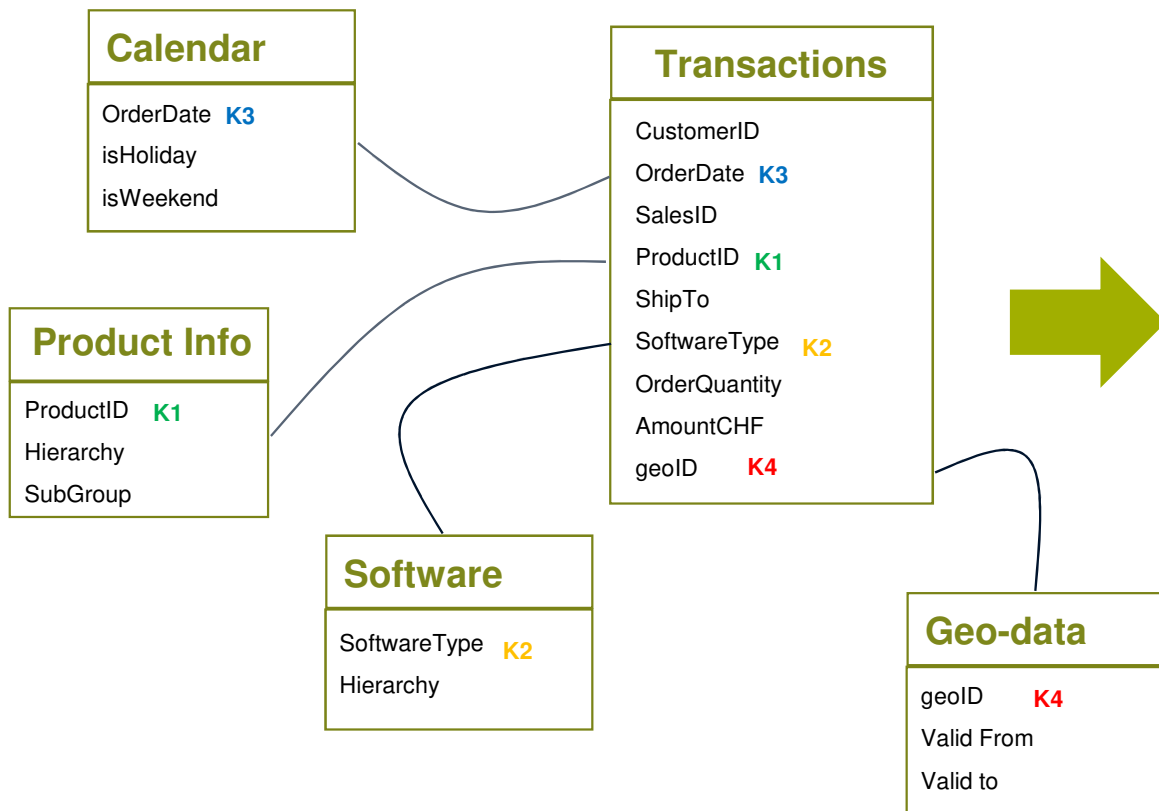
- Customer Dimensions
  - ❑ Use Machine Learning to extract new customer dimensions
  
- Customer Geo-Analytics
  - ❑ Leverage geo-data to understand your customers
  
- Predictive Customer Analytics
  - ❑ Predict quantities for your customers

## Customer Dimensions



## Customer Dimensions

- Applicable to: Online shops / Non-profit organizations / B2C
- Goal: Produce new customer dimensions based on transactional data

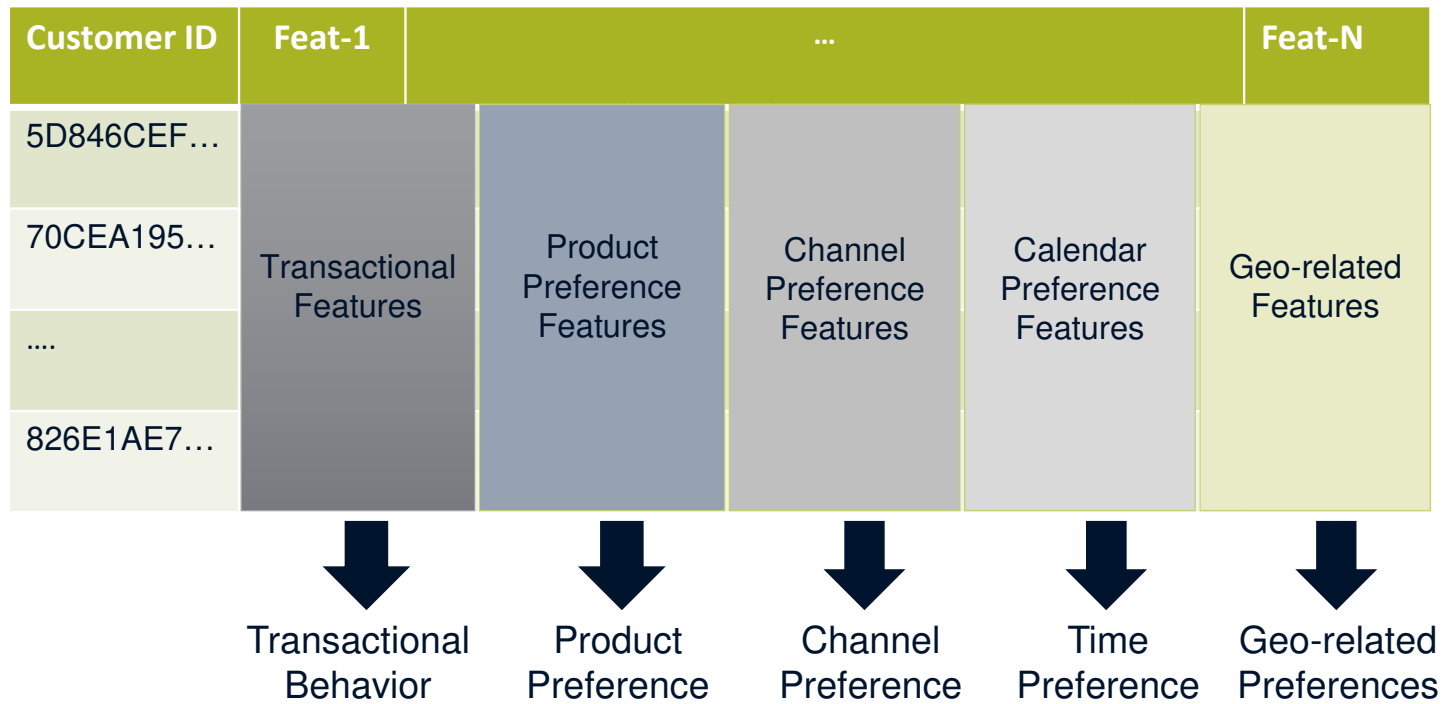


Customer ID	feat1	...	featN
5D846CEF...			
70CEA195...			
....			
826E1AE7...			

- Table / One row for each customer
- More dimensions for each customer

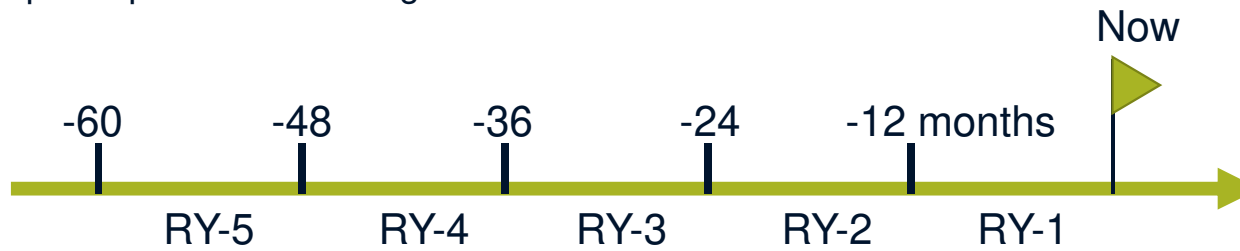
## Customer Dimensions

- › Extraction of more than 100 customer dimensions
- › Great variety of customer dimensions

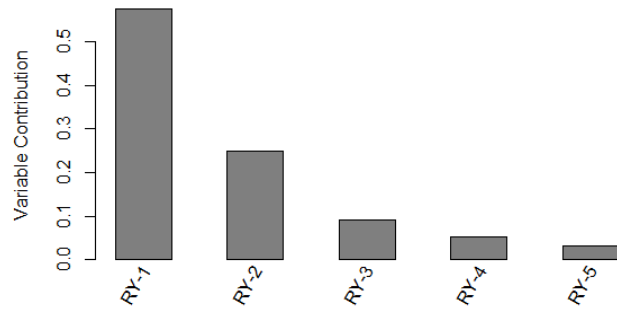


## Customer Dimensions: Examples

### ► Example 1: predictive scoring



CUSTOMER	32 CHF	0 CHF	45 CHF	35 CHF	98 CHF
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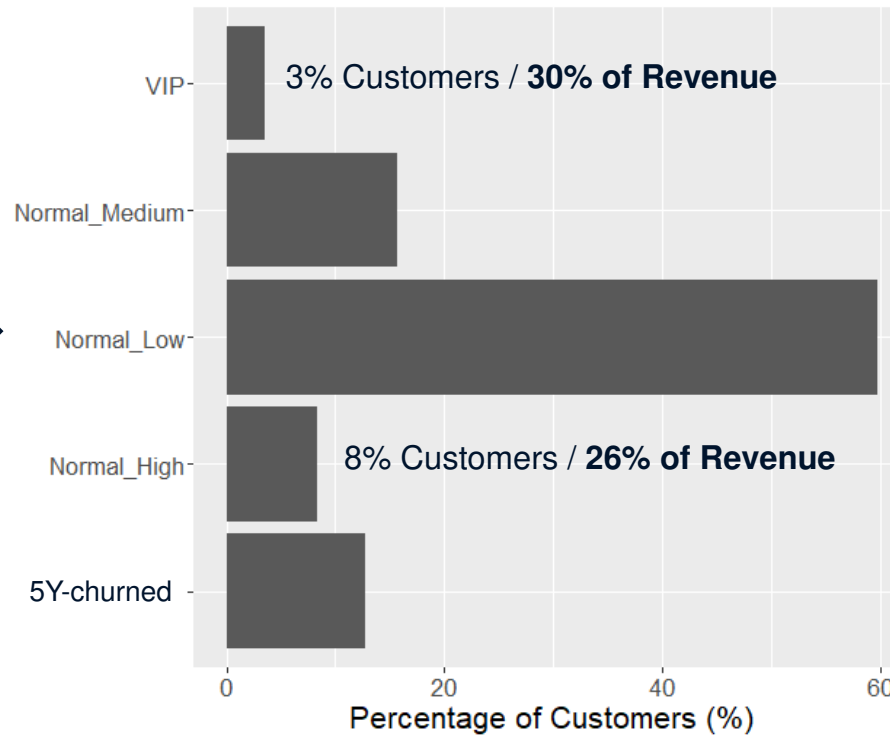
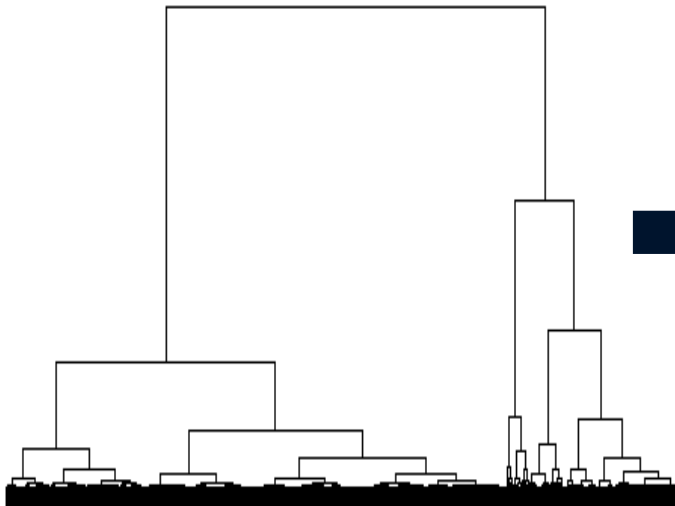


Rolling Year	Weight
Rolling Year 1	0.577
Rolling Year 2	0.249
Rolling Year 3	0.091
Rolling Year 4	0.053
Rolling Year 5	0.030

CUSTOMER SCORE	70.316
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## Customer Dimensions: Examples

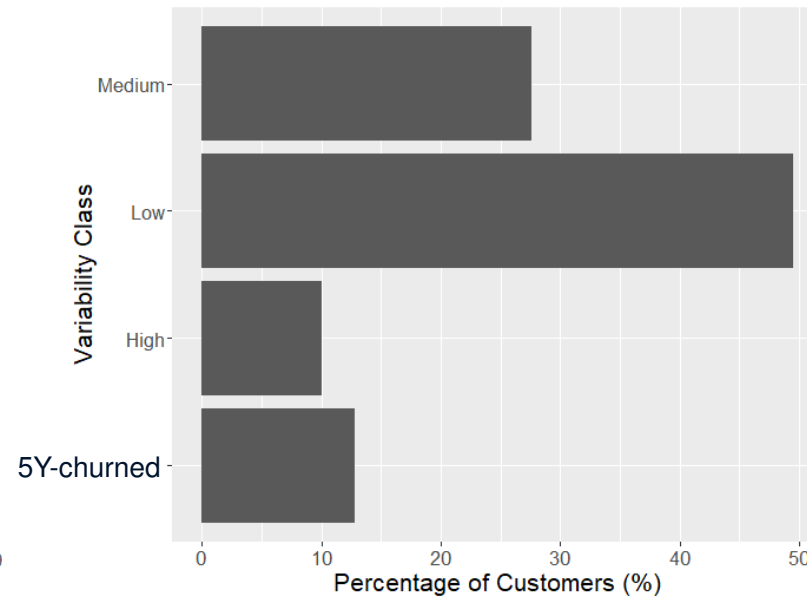
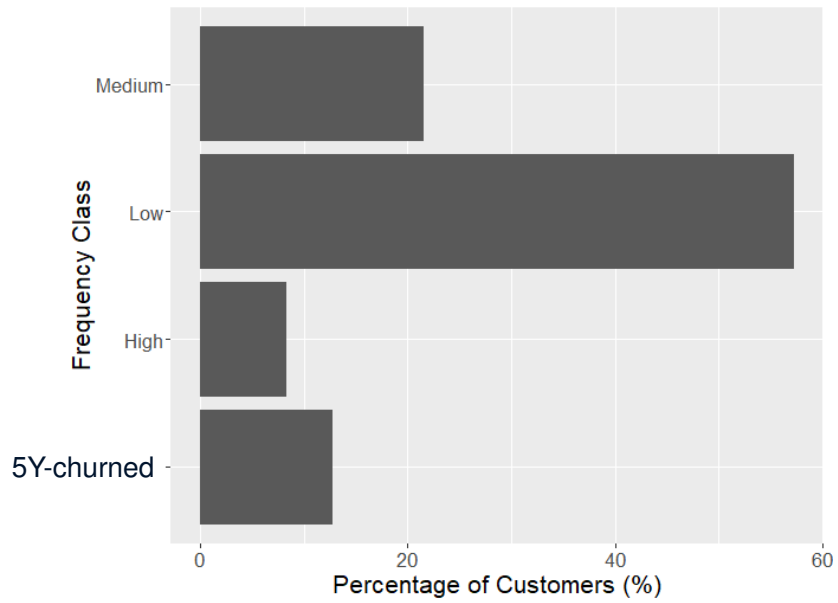
### ► Example 2: Classes





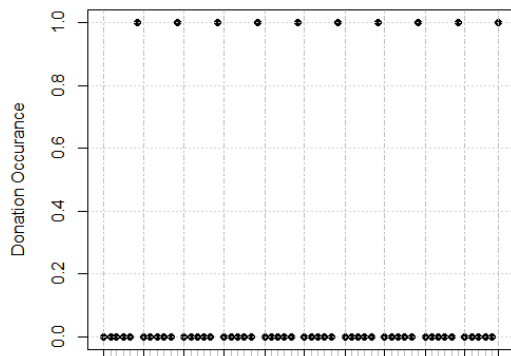
## Customer Dimensions: Examples

### ► Example 2: Classes

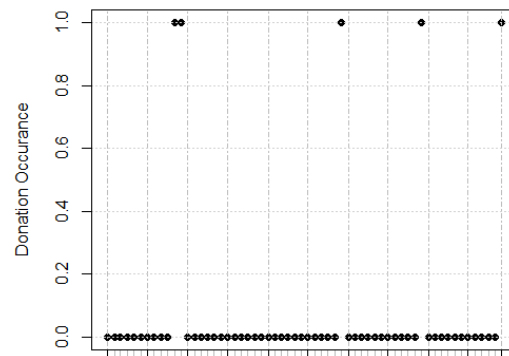


## Customer Dimensions: Examples

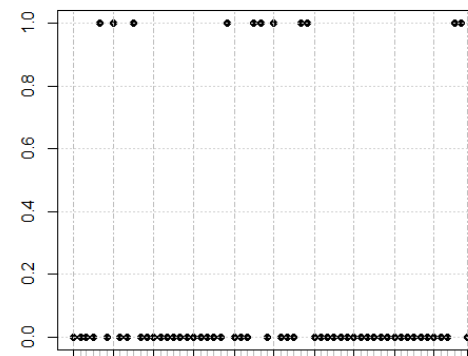
### ➤ Example 3: Periodicity



<b>Periodicity Class</b>	<b>Customer Base (%)</b>
Strong	0.5%



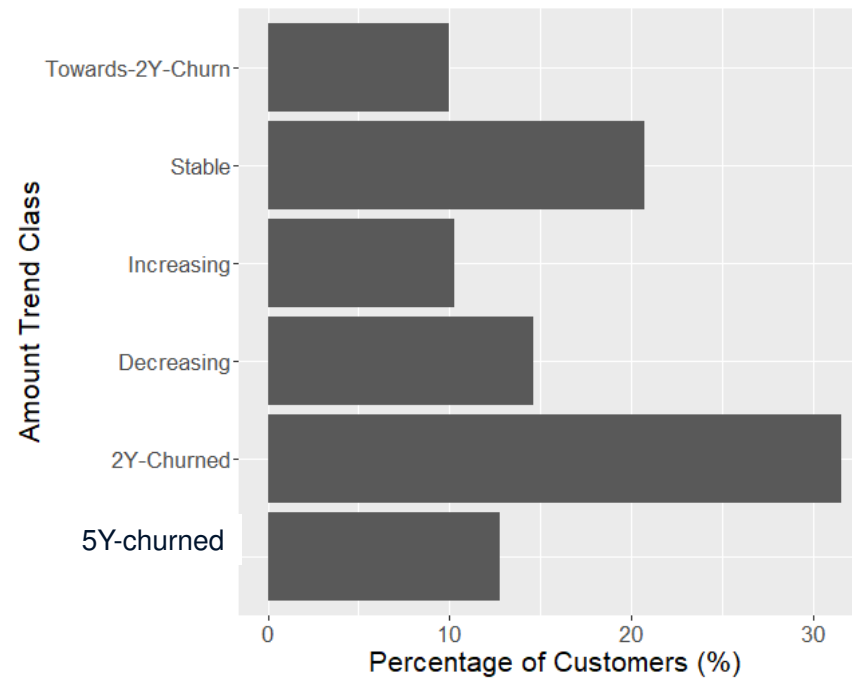
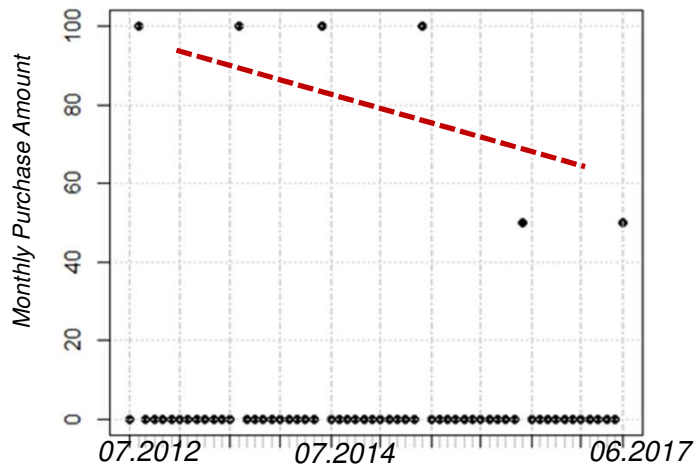
<b>Periodicity Class</b>	<b>Customer Base (%)</b>
Weak	5%



<b>Periodicity Class</b>	<b>Customer Base (%)</b>
Aperiodic	82%

## Customer Dimensions: Examples

### ➤ Example 4: Trends



## Customer Dimensions: Use

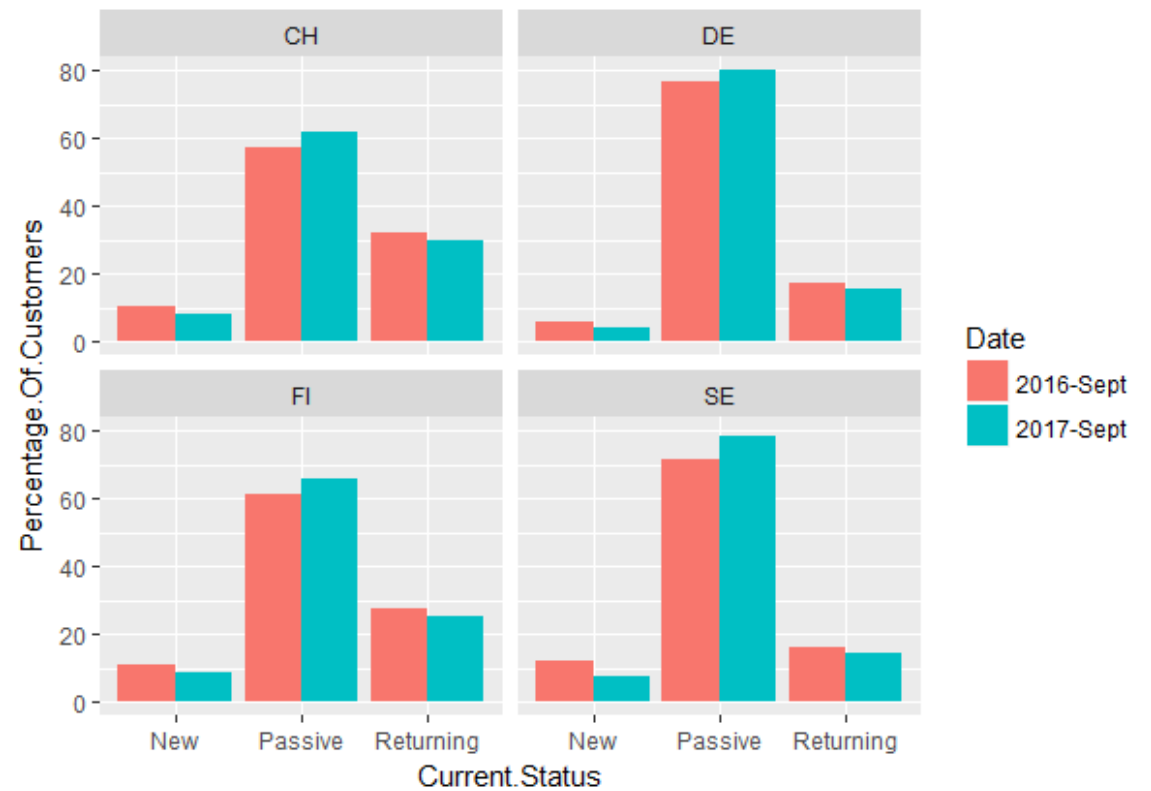
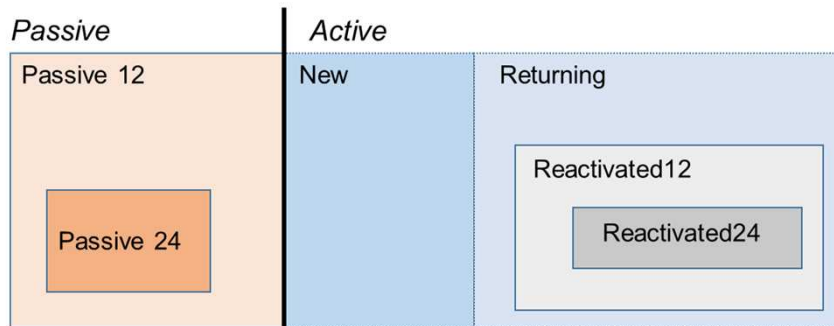
### ➤ Customer Behavior Table

Customer ID	Feat-1	...			Feat-87
5D846CEF...	Transactional Features	Product Preference Features	Channel Preference Features	Calendar Preference Features	Geo-related Features
70CEA195...					
....					
826E1AE7...					

- Descriptive statistics
  - ❑ E.g. for reports/dashboards/pivot tables, etc
- Customer segments
  - ❑ Create customer groups on-the-fly, monitoring
- Input for predictive models
  - ❑ e.g. churn, retention, offer acceptance, promotion of trips, etc

## Customer Dimensions: Descriptive Statistics

### › Descriptive statistics



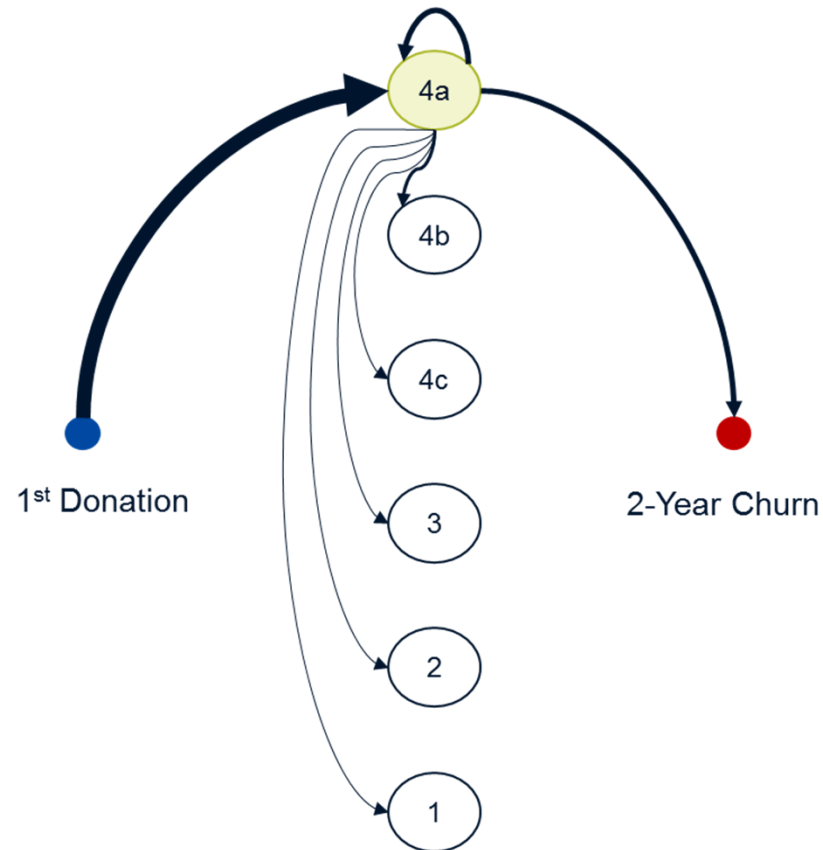
## Customer Dimensions: Customer segments

### Customer Segments

ID	Features	Population (%)	Revenue (%)
4a	Amount_Group= Normal_low Nr. Of Reactions 5Y = 1	30%	5.5%
4b	Amount_Group= Normal_low Nr. Of Reactions 5Y > 1 Frequency = Low Periodicity = Aperiodic	33%	14%
4c	Amount_Group= Normal_Low Nr. Of Reactions 5Y > 1 Frequency = Medium, High   Periodicity = weak, strong	22%	14%
3	Amount_Group = Normal_Medium	13%	28%
2	Amount_Group = Normal_High	2%	10%
1	Amount.Class = Special	1%	30%

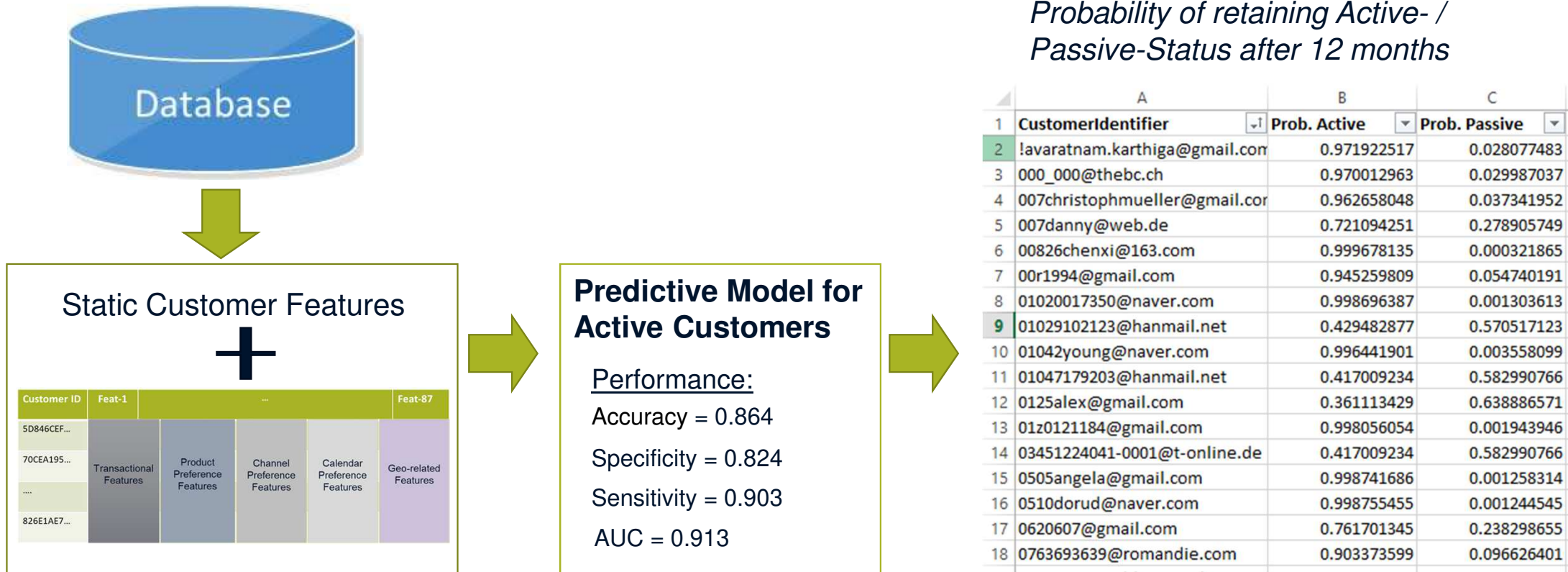
ID	Features	Population	Revenue (%)
3p	Periodicity = Strong,Weak Frequency = Low	2.6%	5.4%

ID	Features	Population	Revenue (%)
3f	Frequency = Medium, High	7.2%	15 %



## Customer Dimensions: Predictive models

### ► Predictive models



## Customer Geo-Analytics





## Geo-data in Switzerland

### › BFS as a source of information

#### Regional Level

State  
(Kanton)

District  
(Bezirk)

Community  
(Gemeinde)

Hectare  
(100m x 100m)



#### Features / Attributes

- Age groups
- Housing Information
- Country of origin
- Marital status
- Language
- Work sectors
- Family and kids
- Religion
- Political opinions
- Commuting
- Urbanization
- Educational level
- Income
- etc

# Geo-data in Switzerland

## ➤ BFS as a source of information

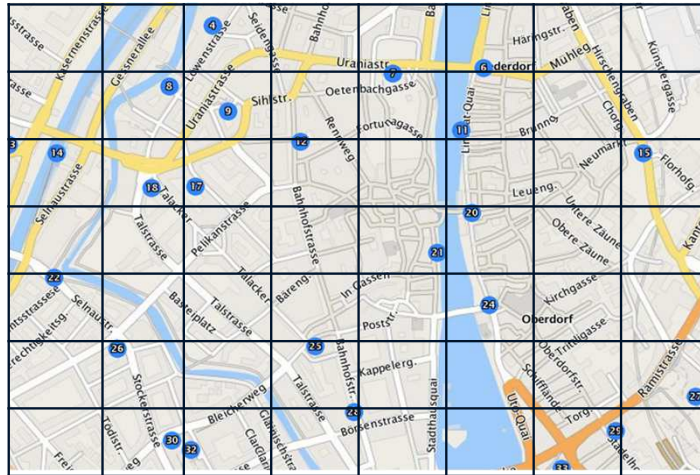
### Regional Level

State  
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Hectare  
(100m x 100m)

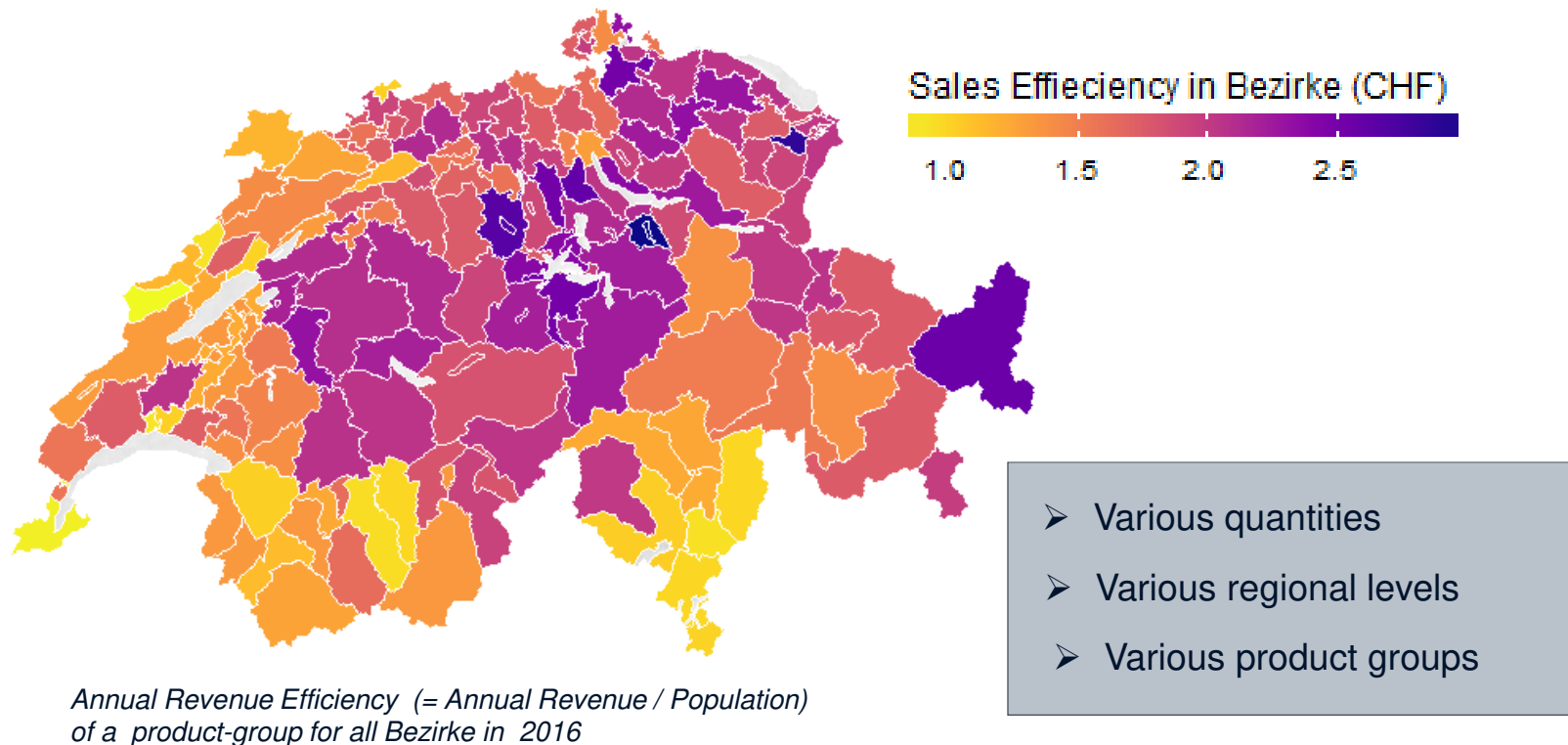


### Features / Attributes

- Age groups
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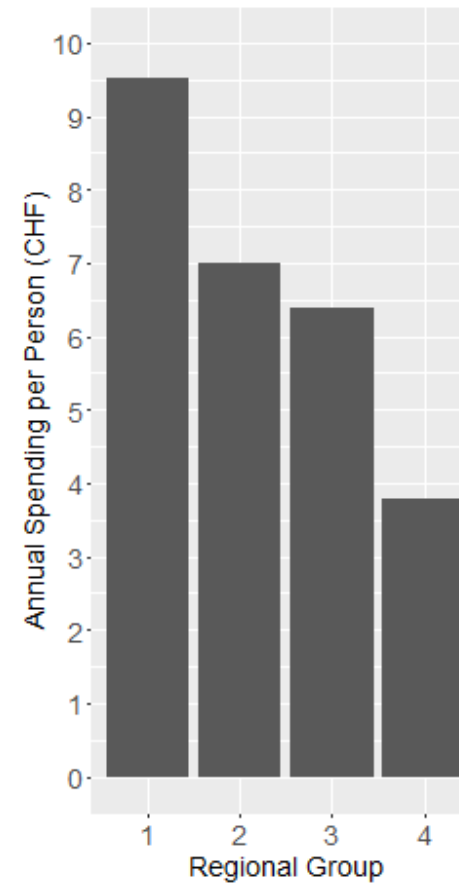
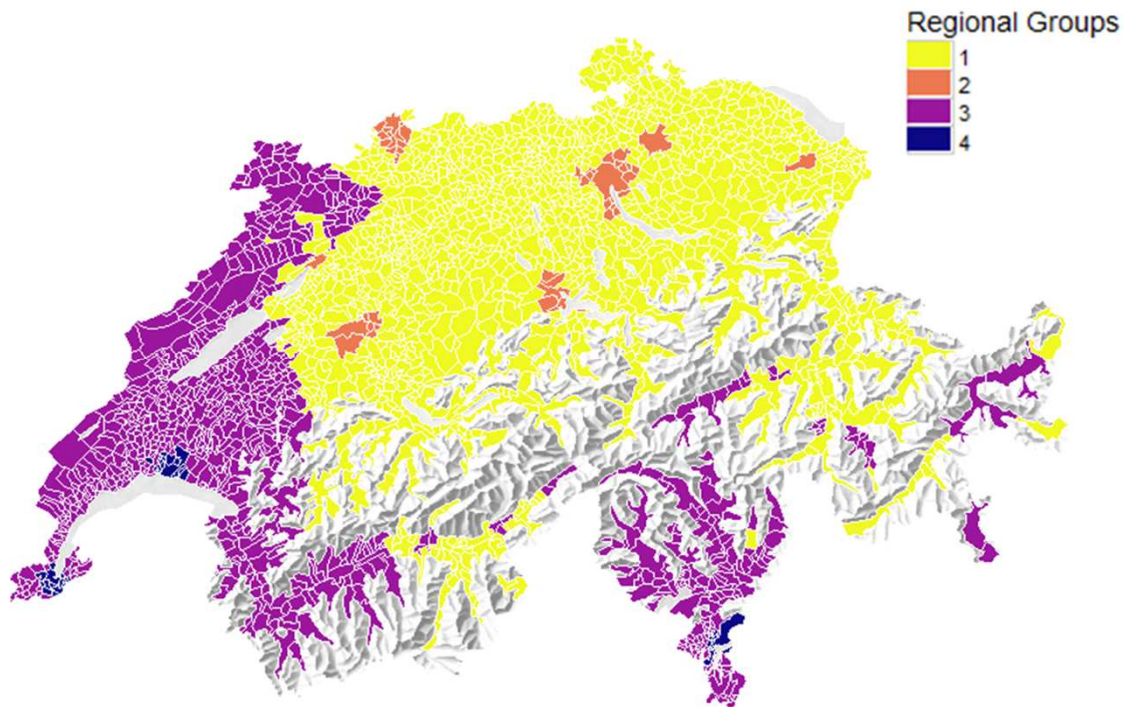
## Customer Geo-Analytics: Results

- Quantification sales efficiency at the regional level



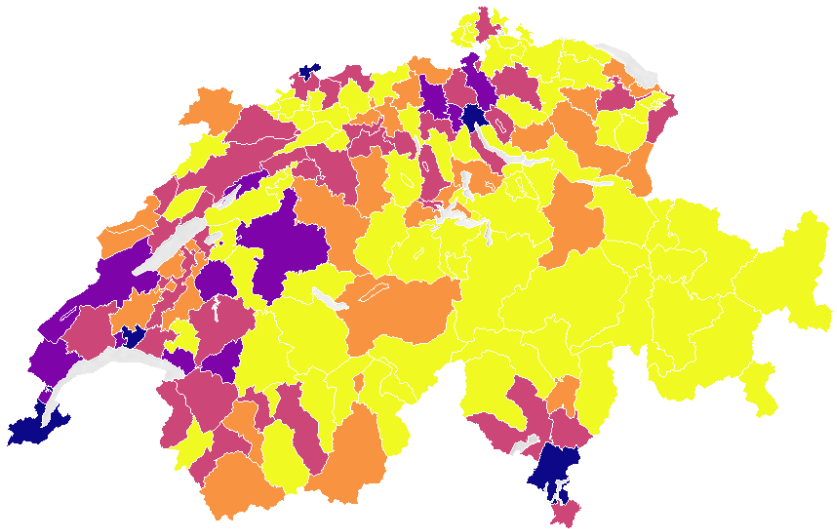
## Customer Geo-Analytics: Results

### ➤ Regional grouping



## Customer Geo-Analytics: Results

### ➤ Annual revenue potential



Revenue Potential (CHF)



*Annual revenue potential of a product-group at the Bezirk-level*

Which regions should be targeted first?

Kanton	Revenue Potential (in '000s CHF)	Cumulative Percentage (%)
Vaud	569	14.2
Genève	558	28.1
Zürich	539	41.6
Ticino	347	50.3
...	...	...

*Annual revenue potential of a product-group at the Kanton level*

# Customer Geo-Analytics: Diversity of Geo-data in CH

➤ BFS as a source of information

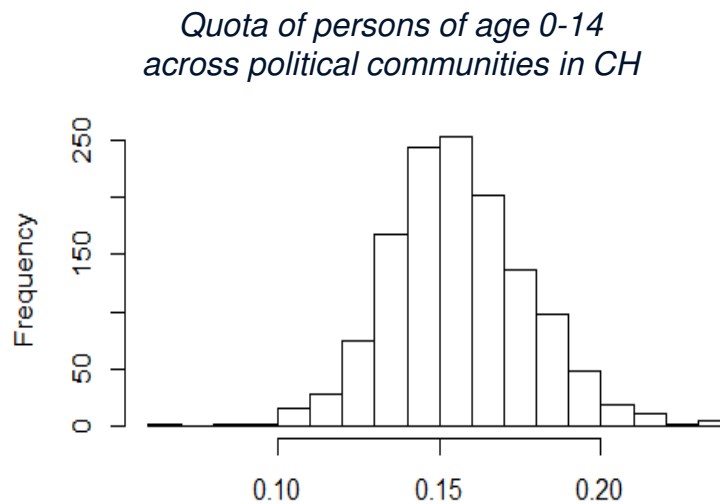
## Regional Level

State  
(Kanton)

District  
(Bezirk)

**Community  
(Gemeinde)**

Hectare  
(100m x 100m)



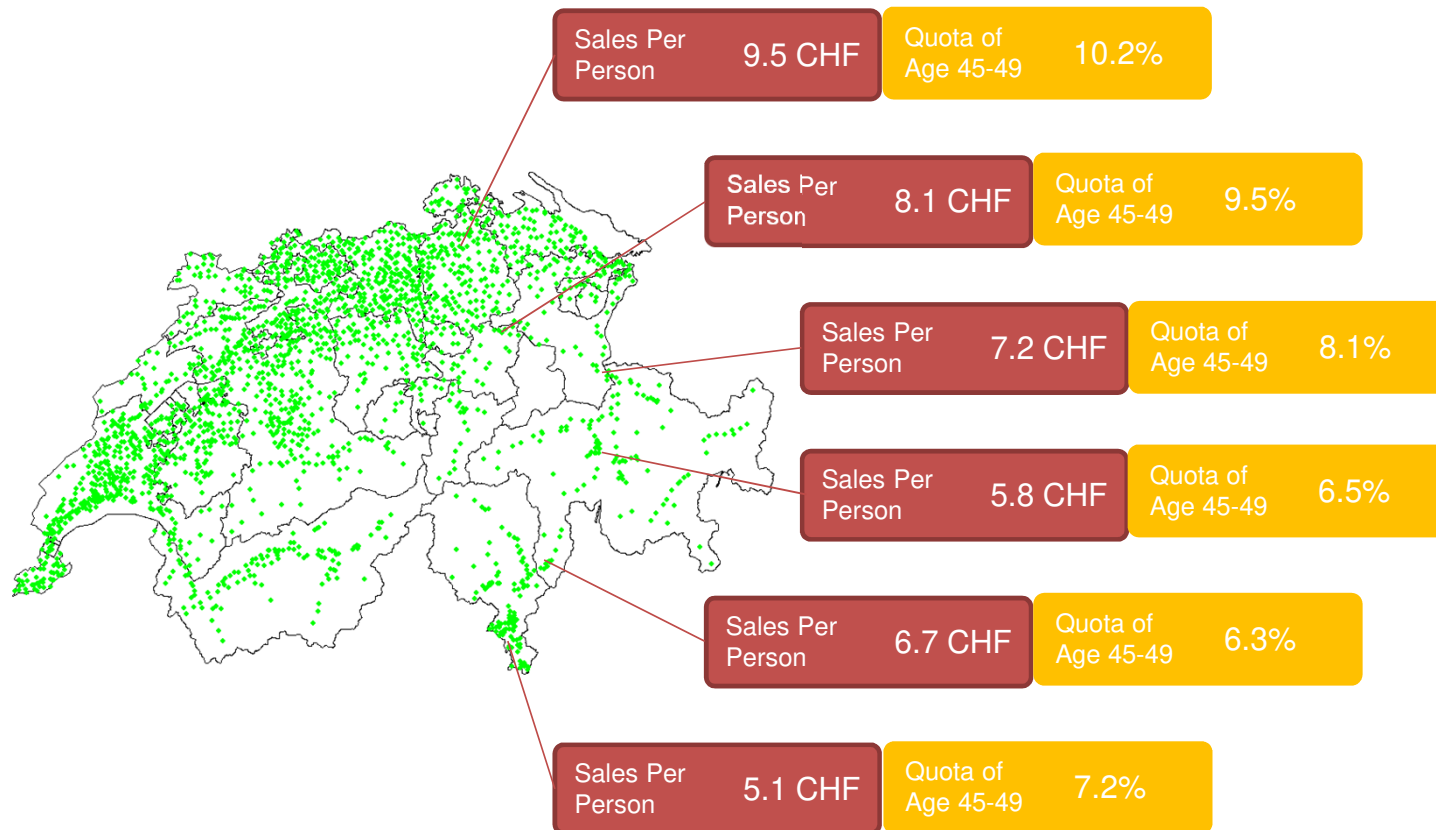
Diversity is the key to informativeness!

## Features / Attributes

- **Age groups**
  - 0-4
  - 5-9
  - **10-14**
  - 15-19
  - 20-24
  - ...
  - 89 and more
- Housing Information
- Country of origin
- Marital status
- Language
- Work sectors
- etc

## Customer Geo-Analytics: Results

- Analysis for age-groups: exploit regional diversity



## Customer Geo-Analytics: Results

- Analysis for age-groups: exploit regional diversity

Independent Variables                      Response Variable

↓    ↓

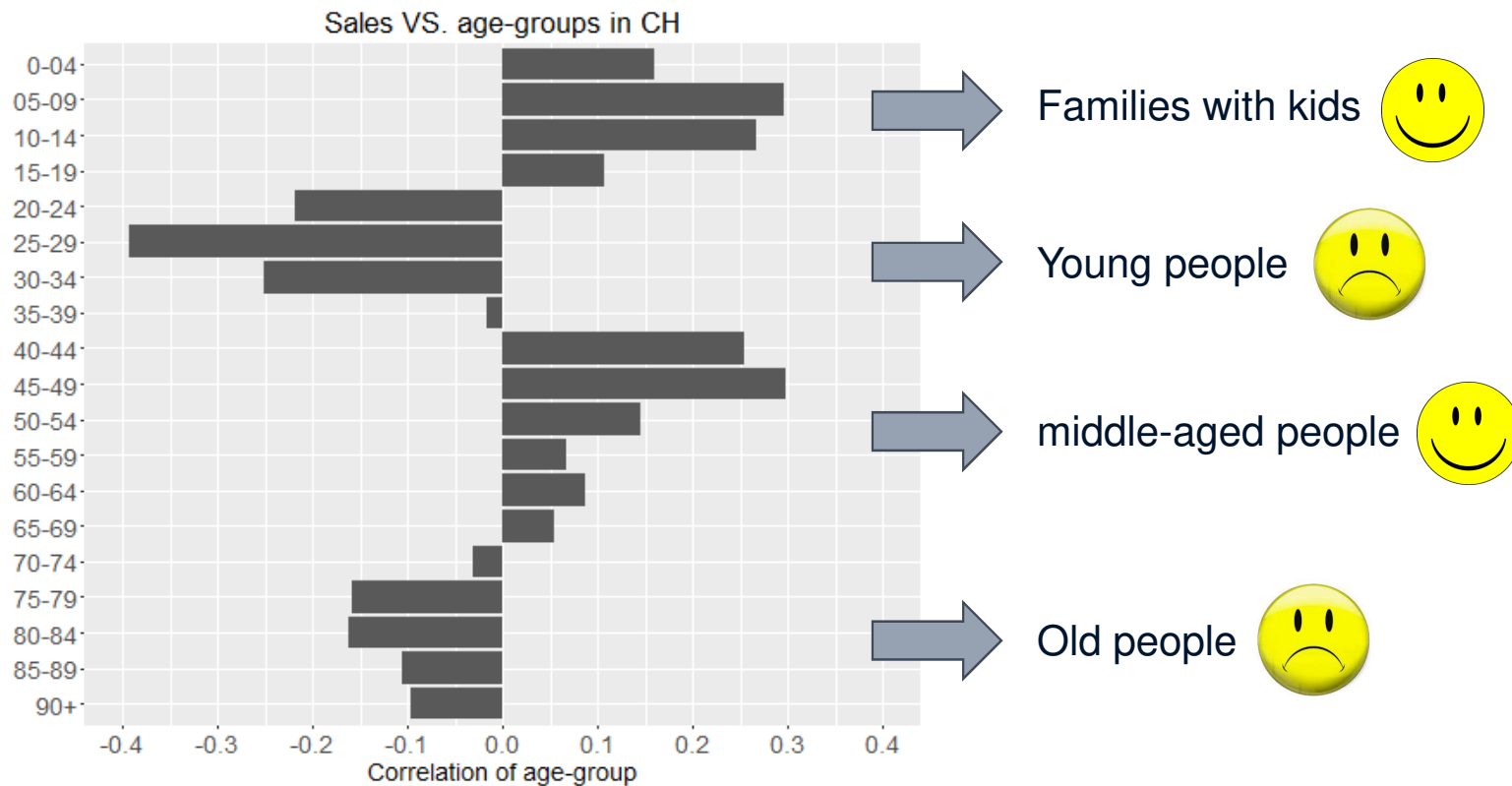
Region ID	Name	Age Demographics						Sales
1006	Bezirk Sense	0.143895	0.181273	0.978240	0.372817	0.544616	7.28	
1002	District de la Glâne	0.135870	0.191506	0.942876	0.396533	0.399811	6.28	
109	Bezirk Uster	0.185181	0.225751	0.994931	0.310582	...	1.055710	5.57
110	Bezirk Winterthur	0.151051	0.475483	0.976424	0.284481	0.676363	6.35	
1402	Bezirk Reiat	0.179851	0.406456	0.856140	0.251028	0.810297	2.81	
1107	Bezirk Lebern	0.204975	0.353950	0.974240	0.178009	1.159469	11.37	
	⋮	⋮						⋮
1403	Bezirk Schaffhausen	0.126046	0.202425	0.298306	0.377231	1.007837	0.675612	7.61

141



## Customer Geo-Analytics: Results

### ► Sales Efficiency for age-groups

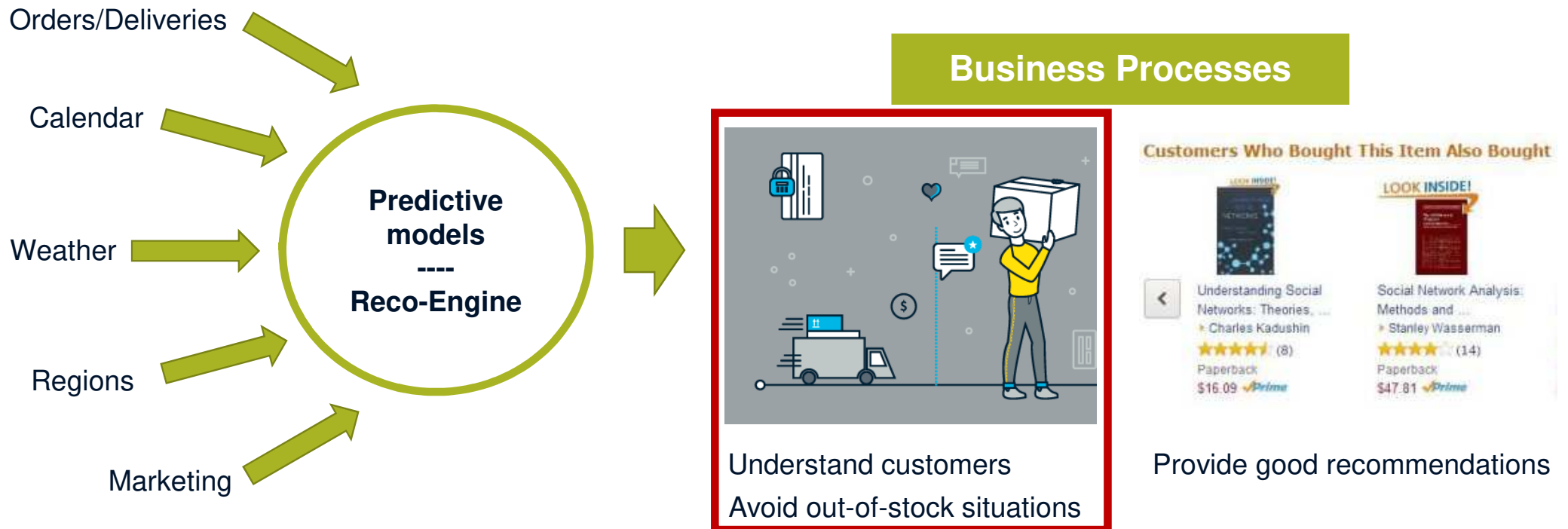


## Predictive Customer Analytics



## Predictive Customer Analytics: Business Perspective

- Client: Retailer of drinking products
- Logistics Department for **H**otels-**R**estaurants-**C**atering (HoReCa)



## Predictive Customer Analytics: Predictive models

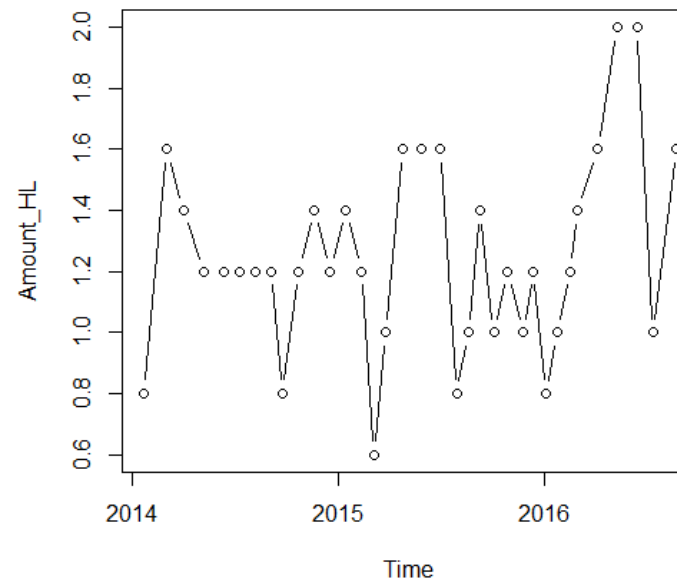
- ▶ Analysis per customer per product

Example: Customer ID = 77 294 025

- 43 deliveries in total
- 29 different products

Product ID	Nr. Of Deliveries
10041	35
10099	32
10152	29
10379	25
10476	24
10514	23
10601	19
10409	14
10153	12
10975	12
10606	10
10448	9
11542	8
11543	7
...	...

We analyzed  
45'360 time-series



- Deliveries start from 2014-01-22
- Amount\_HL in [0.6, 2] HL
- Time interval between consecutive orders in between 14 to 42 days

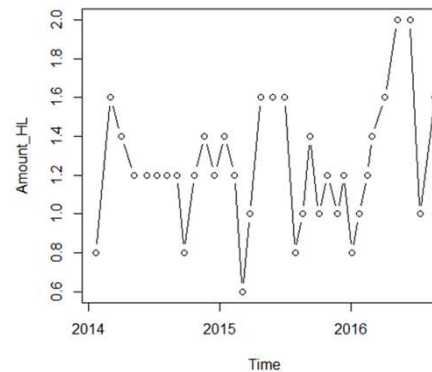
## Predictive Customer Analytics: Predictive models

### ➤ Engaged and non-engaged customers

#### ➤ Gr.1: 972 out of 1579 Customers (62%)

- Patterns exist for at least 1 product of these customers

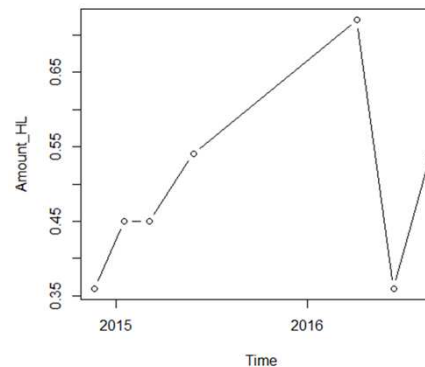
- ✓ **88%** of the total deliveries
- ✓ **83%** of the total express-deliveries



#### ➤ Gr.2: 607 out of 1579 Customers (38%)

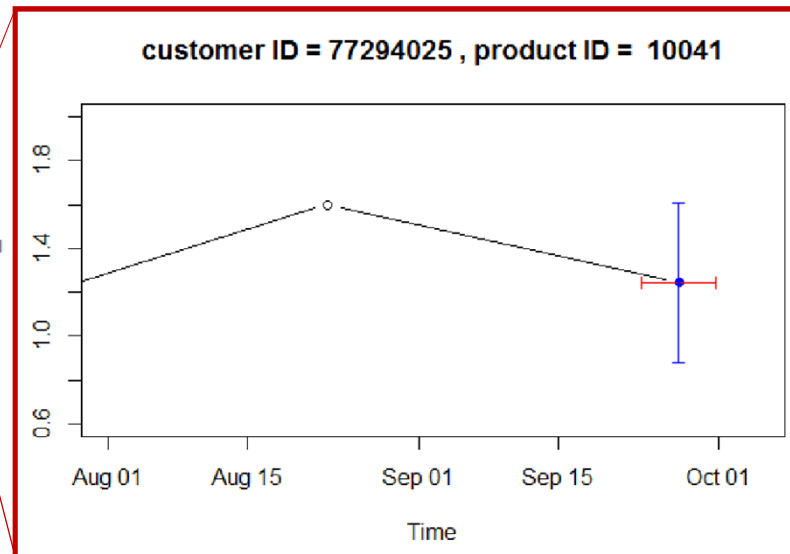
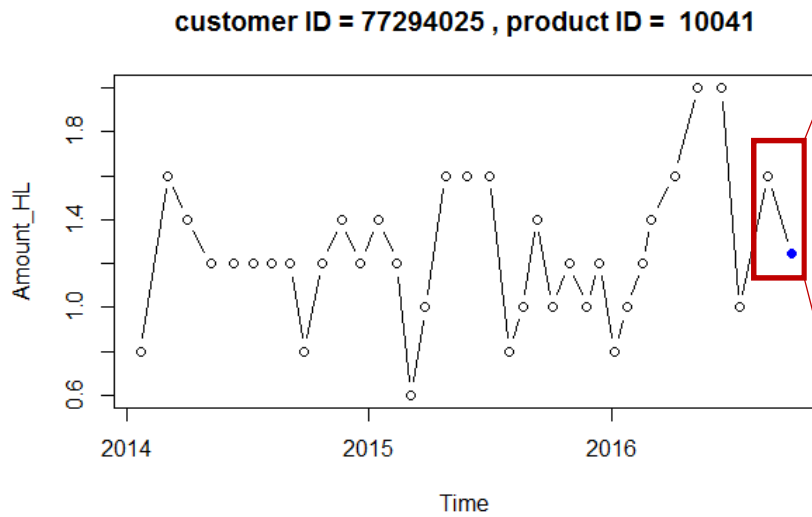
- Patterns do not exist  
(at least based on the history of deliveries)

- Example: Between all consecutive orders  
Min Day Difference = 49  
Max Day Difference = 313



## Predictive Customer Analytics: Predictive models

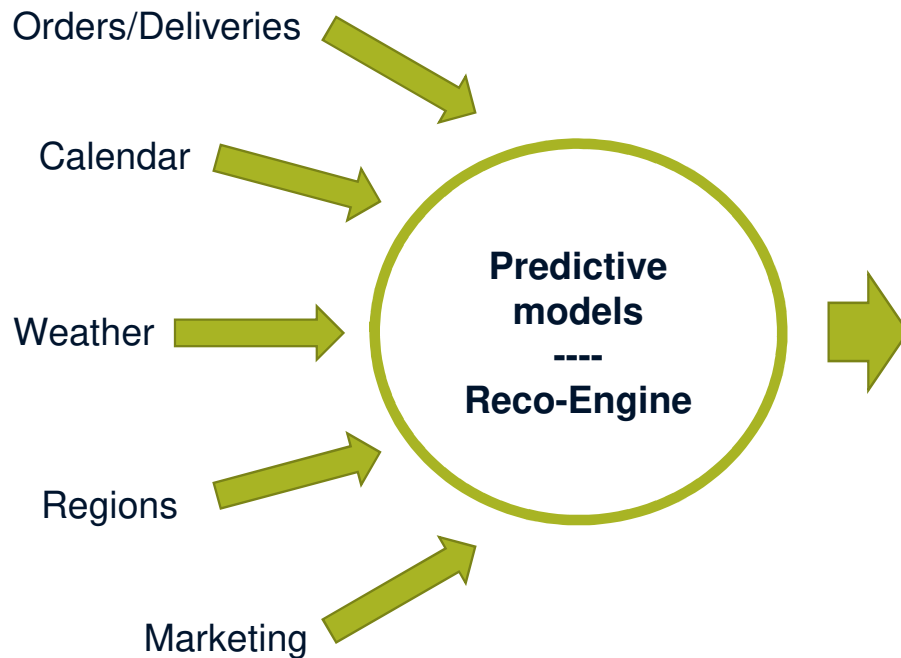
### Engaged customers (Gr.1): Main Products - Predictions



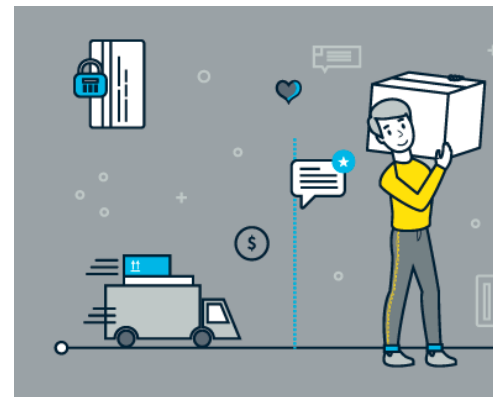
Predict order-date of customer based on the main product

## Predictive Customer Analytics: Business Perspective

- Client: Retailer of drinking products
- Logistics Department for **H**otels-**R**estaurants-**C**atering (HoReCa)



### Business Processes



Understand customers  
Avoid out-of-stock situations

### Customers Who Bought This Item Also Bought



Provide good recommendations

## Predictive Customer Analytics: Recommendations

- › “Past orders” and “current order” of a customer



- › Given the current order, what products shall we recommend???

**1. Intra recommendations** → Based on *current customer's* history of orders & product-consumption

\* Recommended products have been ordered in the past

**2. Inter recommendations** → Based on orders from *similar customers* and *popular combinations* of products

\* Recommended products have NOT been ordered in the past



**DS Products @IT-Logix**



## DS Products @IT-Logix

- Data Science Workshop
  - Explore possibilities with data science
- Auditing of AI/ML models
  - Assess quality of existing AI/ML models
- ML/AI Tutorials and Hands-on Sessions
  - Learn basic concepts of ML and AI
- Requirements Engineering with Data Science
  - Outlier detection via content-based screening
  - Identify important missing quantities



# Data Science for Business

Zürich, Switzerland · 568 members · Public group ?



Organized by  
Sotiris Dimopoulos

17  
OCT

Wednesday, October 17, 2018

## Machine Learning in Enterprise Applications: A Perspective from SAP



Hosted by [Sotiris Dimopoulos](#)  
From [Data Science for Business](#)  
Public group ?

You're going 37 people going



Share:

### Details

#### Agenda:

- 18:00 Introduction & welcome, Dr. Sotiris Dimopoulos, IT Logix
- 18:10 Machine learning in enterprise applications: example use cases and approaches, Dr. Sean Kask, SAP
- 19:00 Discussion and apéro

#### Short Description of the Talk:

Organizer tools ▾

🕒 Wednesday, October 17, 2018  
6:00 PM to 8:00 PM  
[Add to calendar](#)

📍 Au Premier Bar (Hauptbahnhof)  
Bahnhofplatz 15 · Zürich  
**How to find us**  
Meeting room "Les Trouvailles"

## Wir freuen uns auf angeregte Gespräche mit Ihnen

- › Sotiris Dimopoulos, PhD  
Senior Data Science Consultant

