ON4OFF – Status Künstliche Intelligenz

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09.09.2020 Zurbrüggen Möbel, Unna, Deutschland

ON4OFF - Forschungsprojekt

adesso

JÜLICH Forschungszentrum

Hochschule Niederrhein
University of Applied Sciences

IN-telegence

UNIVERSITÄT DUISBURG ESSEN
Offen im Denken

PARFÜMERIE Pieper

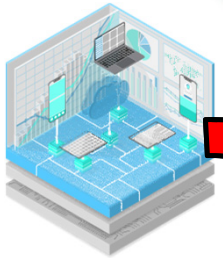
Schlagworte

Künstliche Intelligenz

Maschinelles Lernen

Big Data

Deep Learning



Personalisiert & Individuell

Stationärer Einzelhandel

High Performance Computing & Cloud Computing

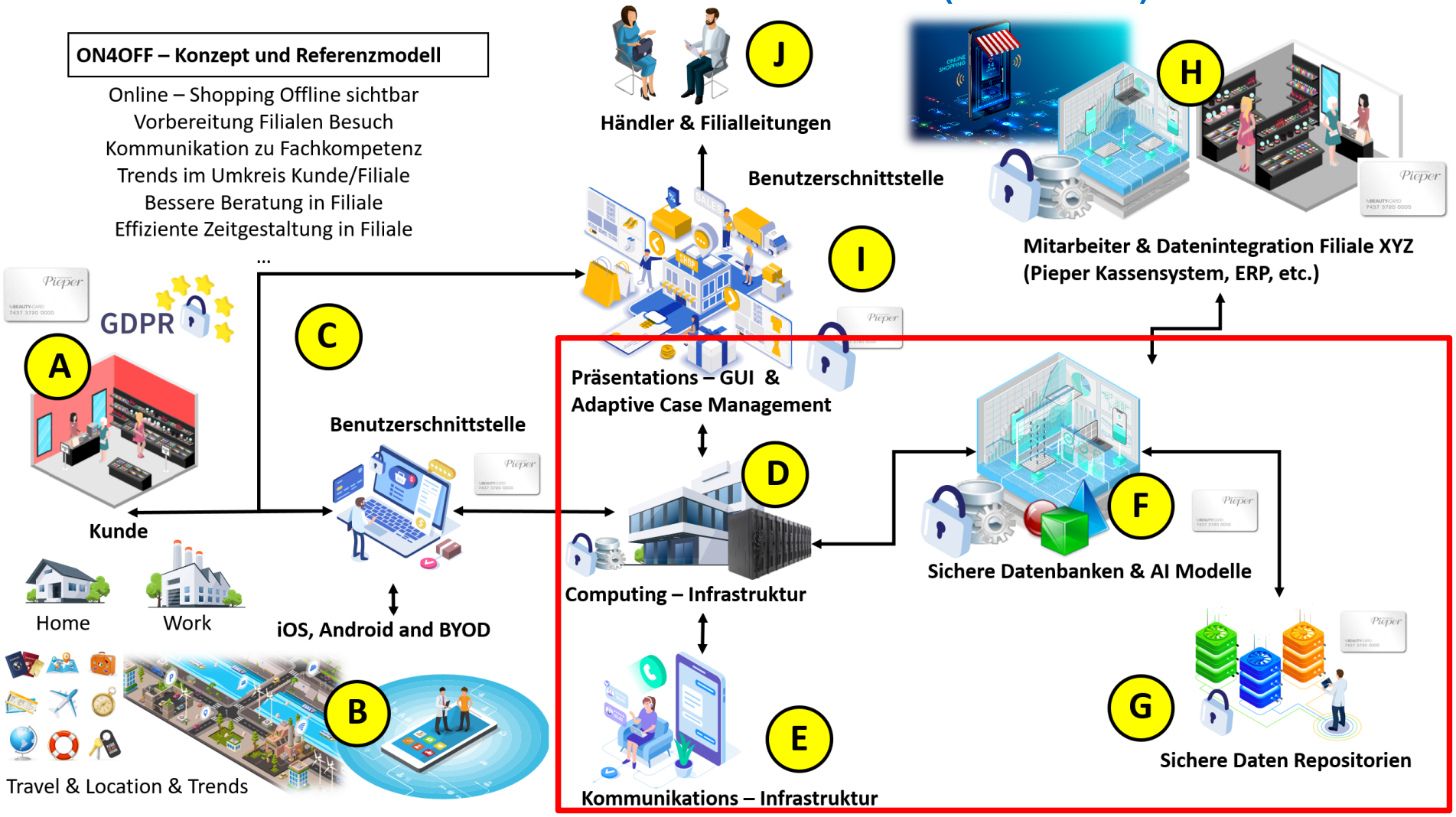
Customer Journey & Einkaufserlebnis

Seamless Shopping

Cross Channel

Modular Supercomputing

ON4OFF Referenzmodell für den Einzelhandel (KI Fokus)



KI Modell #1 – Erzeugung automatischer Tag-Begriffe für Produkte in DE

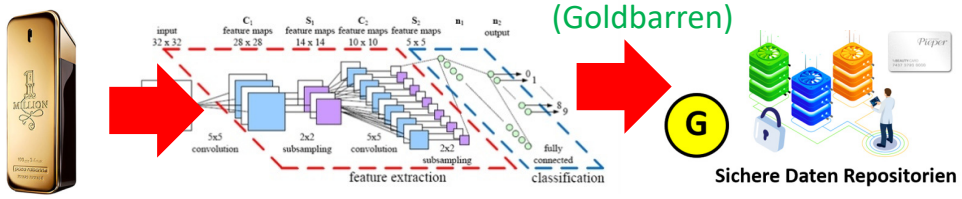
Übersicht KI Modelle in ON4OFF

Künstliche Intelligenz (KI)

Maschinelles Lernen (ML)

Deep Learning (DL)

Modell #1 - Erzeugung automatischer Tag-Begriffe für Produkte in DB

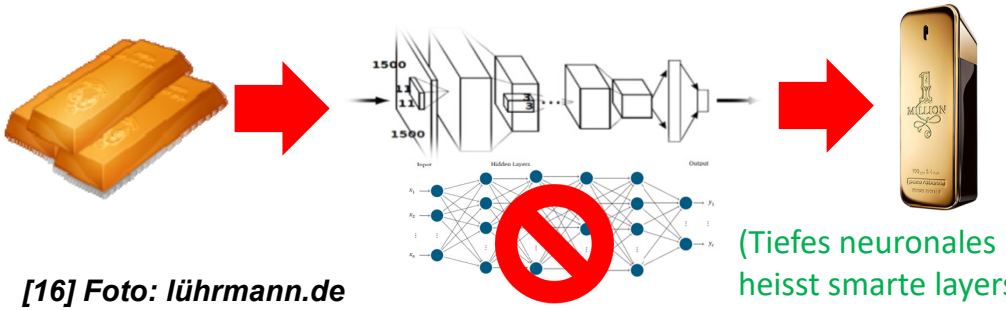


Modell #1 - Erzeugung automatischer Tag-Begriffe für Produkte in DB

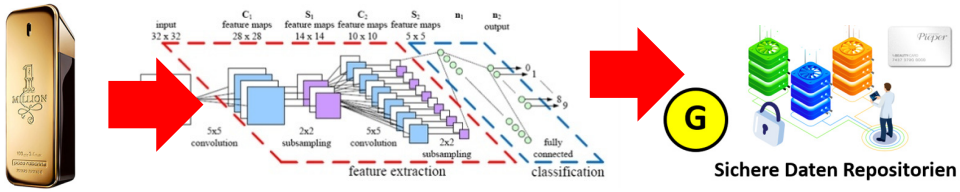
(Ich suche ein Parfum das sieht aus wie ein Goldbarren…)

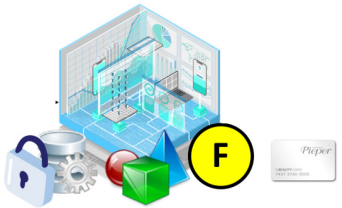
- ✓ Vortrainiertes RESNET-50 Netzwerk auf 14 Mio Bilder (ImageNet Bilder frei verfügbar)
- ✓ 3-4 Stunden Aufwand, nicht sehr komplex (Fine-tuning mit RESNET-50 etwas mehr)
- ✓ Einmal trainiert, braucht kaum Rechenzeit
- ✓ Adaptierbar auf Ihre Produktpalette
- ✓ Top 1-5 Treffer denkbar (nicht nur Hauptbegriff - auch Nebenbegriffe)

(Neuartige tiefe Neuronale Lernnetze zur Bilderkennung …)



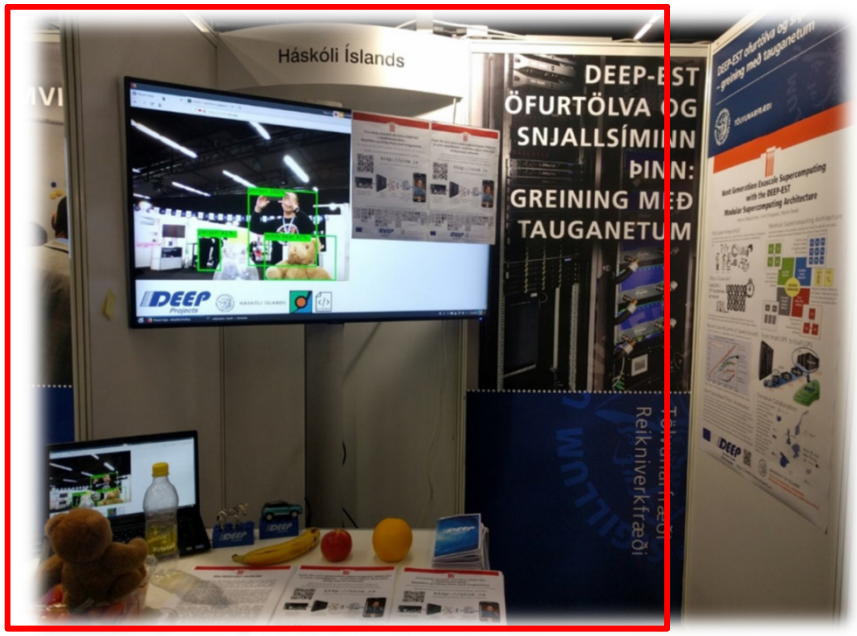
(Tiefes neuronales Netzwerk heisst smarte layers, nicht nur Neurons)



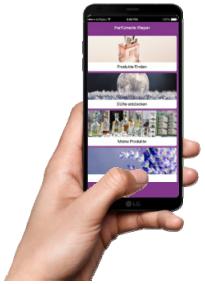


[16] Foto: lührmann.de

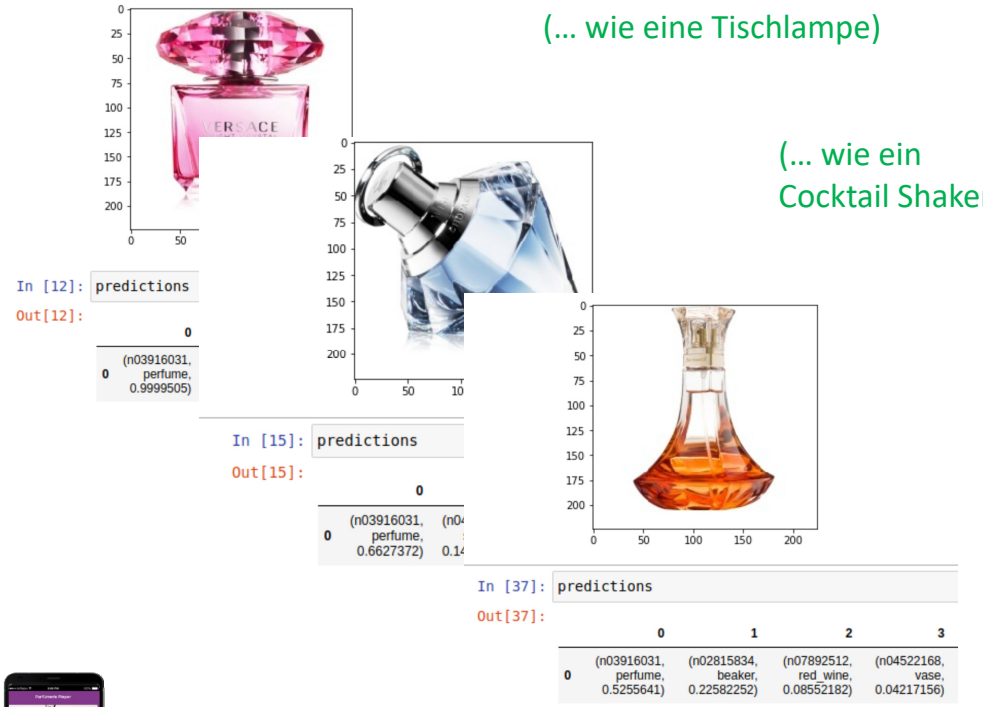
Modell #1 - Erzeugung automatischer Tag-Begriffe für Produkte in DB



[15] DeepSense.ai, 'Produkterkennung'



(Nächster Schritt bspw.: Wo ist Produkt X bzw. die ähnlichen Produkte bei Ihnen?)



(... wie eine Tischlampe)

(... wie ein Cocktail Shaker)

(... wie ein Rotwein oder Vase; Unterschiede in der Wahrnehmung)

KI Modell #2 – Analyse von Kaufmuster für unpersonalisierte Vorschläge

Übersicht KI Modelle in ON4OFF

Künstliche Intelligenz (KI)

Maschinelles Lernen (ML)

Deep Learning (DL)

Modell #2 – Analyse von Kaufmuster für unpersonalisierte Vorschläge

```
0,1,2,3,4,5,6
HugoBoss,Chanel,Rituals,Armani,Biotherm,Lancome,Dior
HugoBoss,Biotherm,Armani,Dior,Chanel,Clinique,Lancome
Biotherm,Armani,Rituals,Clinique,Chanel,,
Biotherm,Armani,Rituals,Clinique,Chanel,,
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Armani,Clinique,HugoBoss,,,,
HugoBoss,Clinique,Clinique,,,,
Dior,,,,,,
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Armani,Lancome,Biotherm,HugoBoss,,,
Biotherm,Rituals,Chanel,HugoBoss,Clinique,Lancome,Armani
Rituals,Clinique,Biotherm,Armani,Dior,,
```
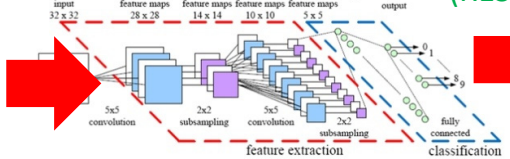

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(Dior)	(Clinique)	0.406349	0.701587	0.260317	0.640625	0.913108	-0.024772	0.830366
1	(Biotherm)	(Clinique)	0.501587	0.701587	0.409524	0.816456	1.163726	0.057617	1.625835
2	(HugoBoss)	(Clinique)	0.504762	0.701587	0.387302	0.767296	1.093657	0.033167	1.282368
3	(Chanel)	(Clinique)	0.438095	0.701587	0.301587	0.688406	0.981212	-0.005775	0.957697
4	(Rituals)	(Clinique)	0.438095	0.701587	0.333333	0.760870	1.084497	0.025971	1.247908
5	(Armani)	(Clinique)	0.476190	0.701587	0.358730	0.753333	1.073756	0.024641	1.209781
6	(Lancome)	(Clinique)	0.361905	0.701587	0.260317	0.719298	1.025244	0.006410	1.063095

(Association Rule Mining via Apriori Algorithmus)

Modell #1 - Erzeugung automatischer Tag-Begriffe für Produkte in DB



(RESNET-50)

KI Modell #2 – Analyse von Kaufmuster für unpersonalisierte Vorschläge

ID	Items
1	{Bread, Milk}
2	{Bread, Diapers, Beer, Eggs}
3	{Milk, Diapers, Beer, Cola}
4	{Bread, Milk, Diapers, Beer}
5	{Bread, Milk, Diapers, Cola}
...	...

market basket transactions

{Diapers, Beer} Example of a frequent itemset

{Diapers} → {Beer} Example of an association rule

[2] mlxtend lib, Apriori

- ✓ Association Rule Mining Algorithmus Apriori genutzt und guter Tool support in MLxtend Bibliothek
- ✓ Einmal „trainiert“, braucht kaum Rechenzeit
- ✓ Im Adesso Server vorhanden & Fakedaten

ToDo: Parameter Fine-Tuning (Confidence, Lift, Support, etc.)

ToDo: Datenauswahl (Ganz Pieper, Filiale, Saison, Tageszeit)

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0,1,2,3,4,5,6
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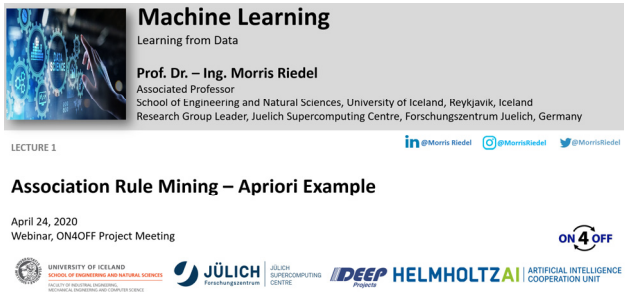
[1] Webinar Slides, ON4OFF Demo
Association Rule Mining – Apriori Example



Demonstrated on Fake-Daten in ON4OFF Webinar on 2020-04-24

KI Modell #3 – Analyse von Kaufmuster für personalisierte Vorschläge

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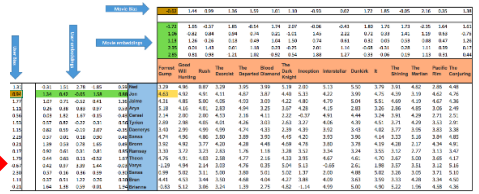
Künstliche Intelligenz (KI)

Maschinelles Lernen (ML)

Deep Learning (DL)

Modell #3 – Analyse von Kaufmuster für personalisierte Vorschläge

	customer_id	product_id	rating
0	1	1193	5
1	1	661	3
2	1	914	3
3	1	3408	4
4	1	2355	5
...	...	...	...
995	10	3704	2
996	10	1020	3
997	10	784	3
998	10	858	3
999	10	1022	5



(Collaborative Filtering)

Modell #2 – Analyse von Kaufmuster für unpersonalisierte Vorschläge

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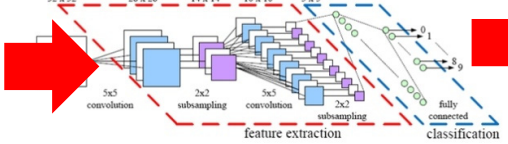
(Association Rule Mining)

Modell #1 - Erzeugung automatischer Tag-Begriffe für Produkte in DB



(Residual Networks)

KI Modell #3 – Analyse von Kaufmuster für personalisierte Vorschläge

```
1::1961::5::978301590
1::1962::4::978301753
1::2692::4::978301570
1::260::4::978300760
1::1028::5::978301777
1::1029::5::978302205
1::1207::4::978300719
1::2028::5::978301619
1::531::4::978302149
1::3114::4::978302174
1::608::4::978301398
1::1246::4::978302091
2::1357::5::978298709
2::3068::4::978299000
2::1537::4::978299620
2::647::3::978299351
2::2194::4::978299297
2::648::4::978299913
2::2268::5::978299297
2::2628::3::978300051
2::1103::3::978298905
2::2916::3::978299809
2::3468::5::978298542
2::1210::4::978298151
2::1792::3::978299941
2::1687::3::978300174
2::1213::2::978298458
2::3578::5::978298958
```

surprise

A Python scikit for recommender systems.

[4] surprise lib, SVD

	customer_id	product_id	rating
0	1	1193	5
1	1	661	3
2	1	914	3
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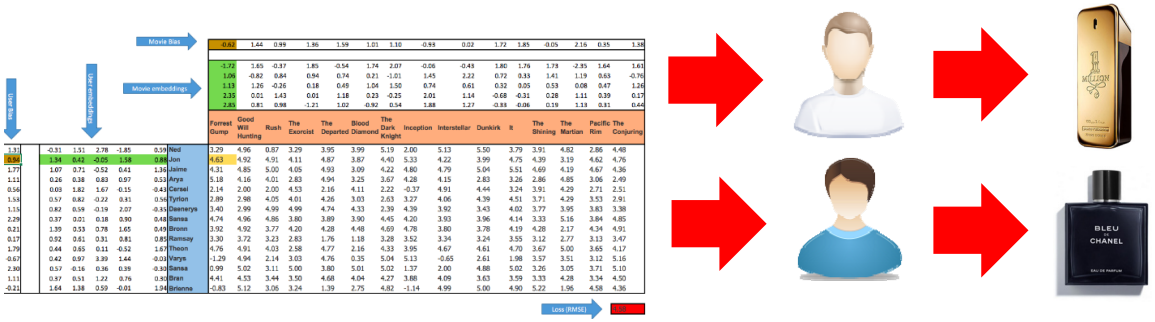
4	1	2355	5
...	...	...	...
995	10	3704	2
996	10	1020	3
997	10	784	3
998	10	858	3
999	10	1022	5

- ✓ Collaborative Filtering Algorithmus SVD genutzt und guter Tool support in SURPRISE Bibliothek
- ✓ Einmal „trainiert“, braucht moderate Rechenzeit

ToDo: Im Adesso Server vorhanden & Fakedaten

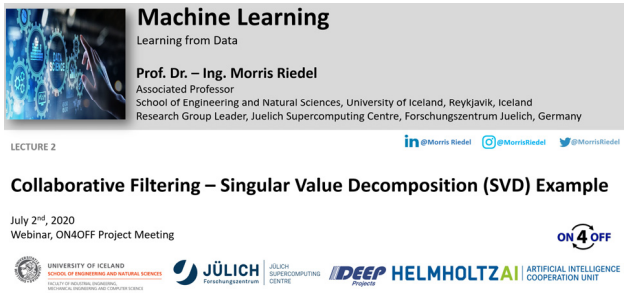
ToDo: Parameter Fine-Tuning & andere Modelle / Algorithmen

ToDo: Datenauswahl (Ganz Pieper, Filiale, Saison, etc.)



(rating kann man unterschiedlich modelieren, also auch Kauf/Verkauf)

[3] Webinar Slides, ON4OFF Demo Collaborative Filtering, SVD Example



Demonstrated on Fake-Daten in ON4OFF Webinar on 2020-07-02

Speedboot & Zusammenfassung

Speedboot Variante #1 – Unpersonalisierte Vorschläge

ON4OFF

Anonymisierte Verkaufsdaten per Händler ohne Kunde

Analyse mit Algorithmen der Künstlichen Intelligenz

Verbesserte Datenauswahl & KI Modell Parameter

Regeln welche Produkte zusammen gekauf werden

Händler Gibt

Transaktionen mit:
Produkt-IDs im Warenkorb

KI Algorithmen

Association Rule Mining
Apriori, FP-Growth, MAFIA

Modell-Tuning

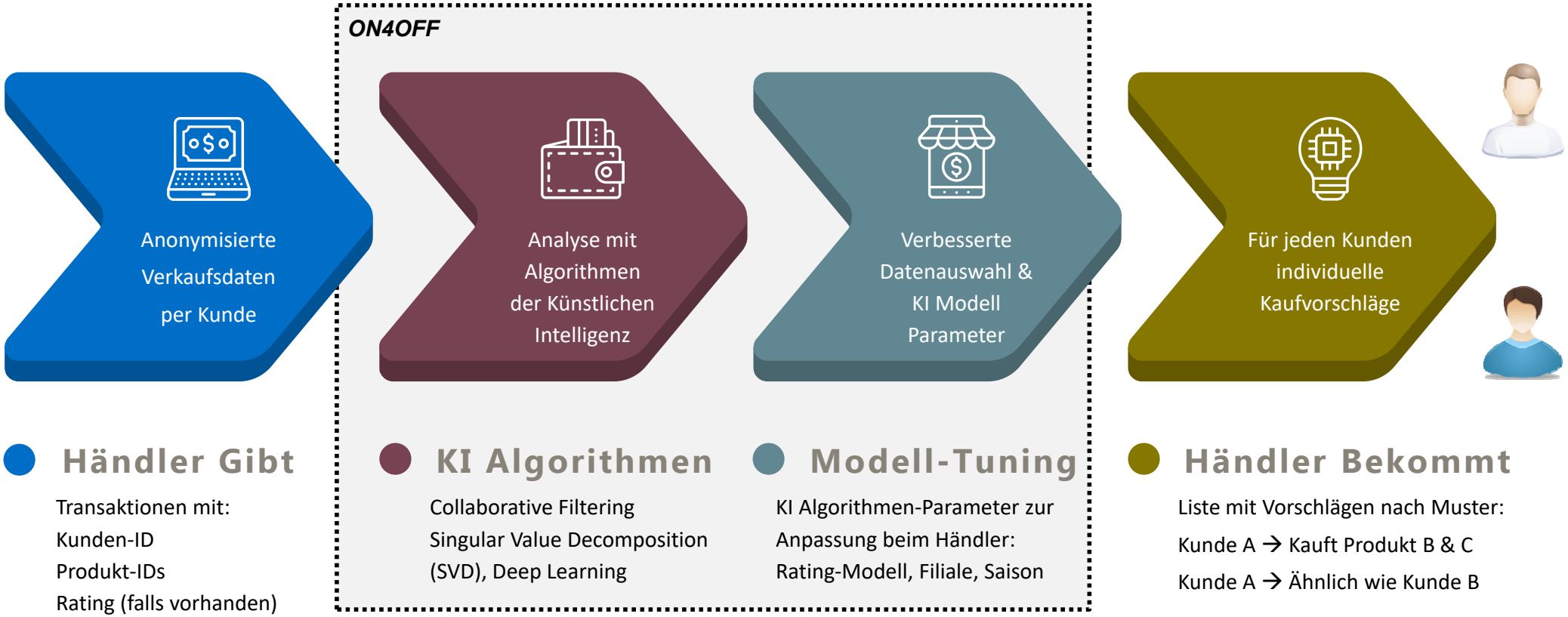
KI Algorithmen-Parameter zur Anpassung beim Händler:
confidence, support, lift, Filiale

Händler Bekommt

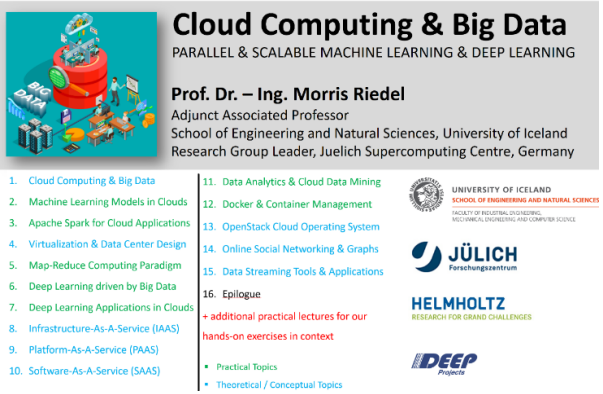
Liste mit Regeln nach Muster:
Gekauft Produkt A → Kauf Produkt B & C
Gekauft Product D & E → Kauf Produkt F

Zeit → ***2-4 Wochen***

Speedboot Variante #2 – Personalisierte Vorschläge



Künstliche Intelligenz – Beratung & Trainings für Assozierte Partner



[10] M. Riedel, 'Cloud Computing & Big Data – Parallel & Scalable Machine Learning & Deep Learning', 2018

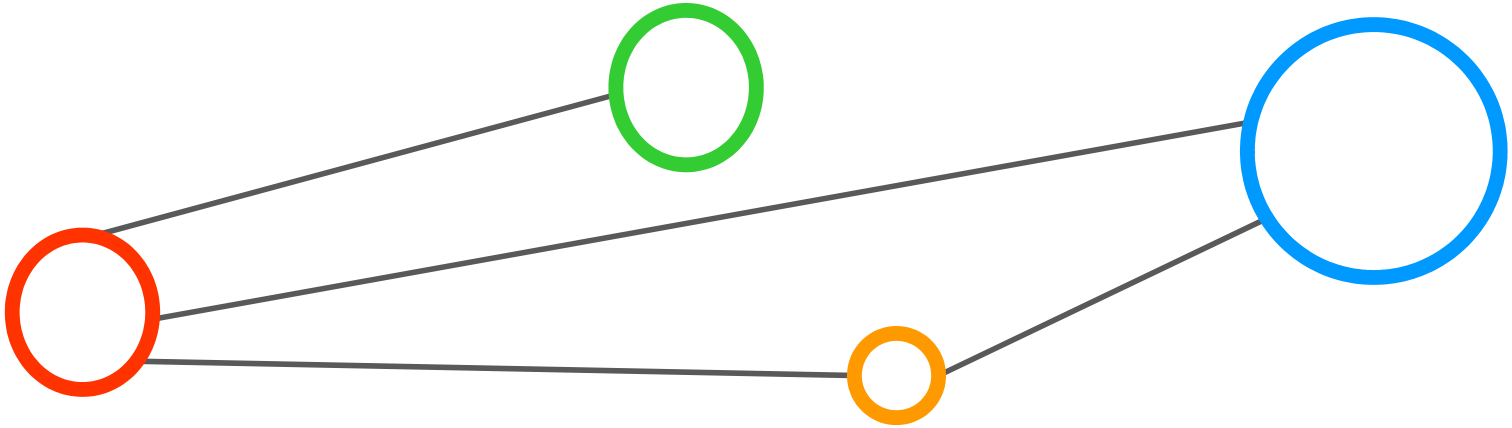
[11] M. Riedel, 'High Performance Computing – Advanced Scientific Computing', 2017

[12] M. Riedel et al., 'DEEP-EST Tutorial: Introduction to Deep Learning', 2018

[13] M. Riedel @ Deutscher Bundestag – German Parliament, 2019

[14] M. Riedel @ European Leadership Network, 2019

Referenzen



Referenzen (1)

- [1] ON4OFF Demo Association Rule Mining – Apriori Example, Online Webinar, ON4OFF Project Meeting, 2020-04-24, Online: http://www.morrisriedel.de/on4off-demo-association-rule-mining-apriori-example
- [2] MLxtend Library, Apriori, Online: http://rasbt.github.io/mlxtend/user_guide/frequent_patterns/apriori/
- [3] ON4OFF Demo Collaborative Filtering – SVD Example, Online Webinar, ON4OFF Project Meeting, 2020-07-02, Online: http://www.morrisriedel.de/on4off-demo-collaborative-filtering-singular-value-decomposition-svd-example
- [4] Surprise Library, SVD, Online: https://www.nvidia.com/en-us/
- [5] Deep Learning Start-Up Beispiel Deutschland, Online: https://soccerwatch.tv/
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