A hybrid quantum-classical recommender system

DATA:LAB
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POWERED BY VOLKSWAGEN GROUP

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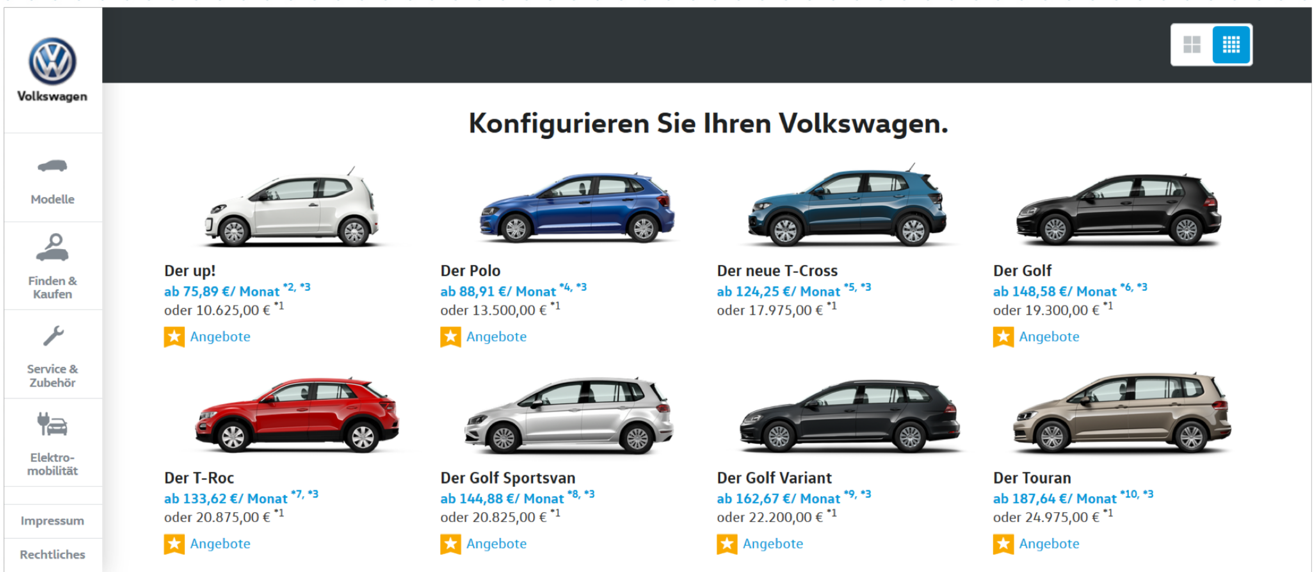
A recommender system built on matrix factorization

- got inspired by nonnegative/binary matrix factorization at Qubits 2018 [1]
- Q: where can we apply NBMF on D-Wave in a Volkswagen context?
- A: recommendations for users of the VW configurator



[1] O'Malley D, Vesselinov VV, Alexandrov BS, Alexandrov LB (2018) Nonnegative/Binary matrix factorization with a D-Wave quantum annealer. PLoS ONE 13(12): e0206653. https://doi.org/10.1371/journal.pone.0206653

SEAT configurator data

	model_5F11E2	model_5F11MX	...	interior_color_BC	SEAT FULL
0	1	1	...	0	0
1	0	1	...	1	1
2	0	0	...	0	1
3	0	0	...	0	1
4	0	0	...	1	0
5	1	0	...	1	1
6	0	0	...	0	0
7	1	0	...	0	0
8	0	1	...	1	1
9	0	0	...	1	1
10	1	0	...	1	1
11	0	0	...	0	0
12	1	1	...	0	0
13	1	0	...	1	1
14	1	0	...	0	0
15	1	0	...	0	1
16	0	0	...	1	0
17	0	0	...	1	1
18	0	1	...	1	0
19	1	0	...	1	1

- data of 47819 car purchases
- data includes color packages, accessories, …
- one-hot encoded categorical features
- turned them into “user ratings”
- 0: no purchase, 5: purchase

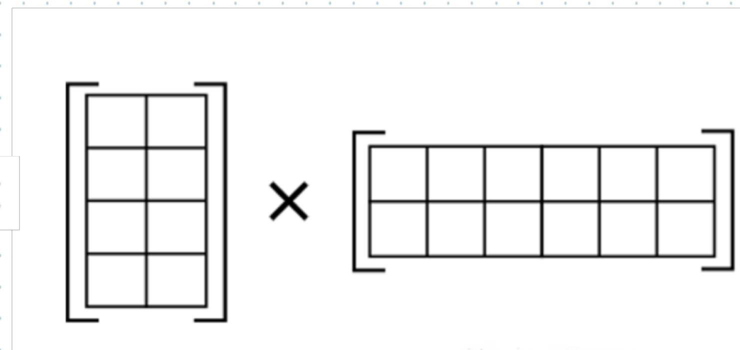
Nonnegative matrix factorization

m

n

	model_5F11E2	model_5F11MX	...	interior_color_BC	SEAT FULL
0	1	1	...	0	0
1	0	1	...	1	1
2	0	0	...	0	1
3	0	0	...	0	1
4	0	0	...	1	0
5	1	0	...	1	1
6	0	0	...	0	0
7	1	0	...	0	0
8	0	1	...	1	1
9	0	0	...	1	1
10	1	0	...	1	1
11	0	0	...	0	0
12	1	1	...	0	0
13	1	0	...	1	1
14	1	0	...	0	0
15	1	0	...	0	1
16	0	0	...	1	0
17	0	0	...	1	1
18	0	1	...	1	0
19	1	0	...	1	1

$=$

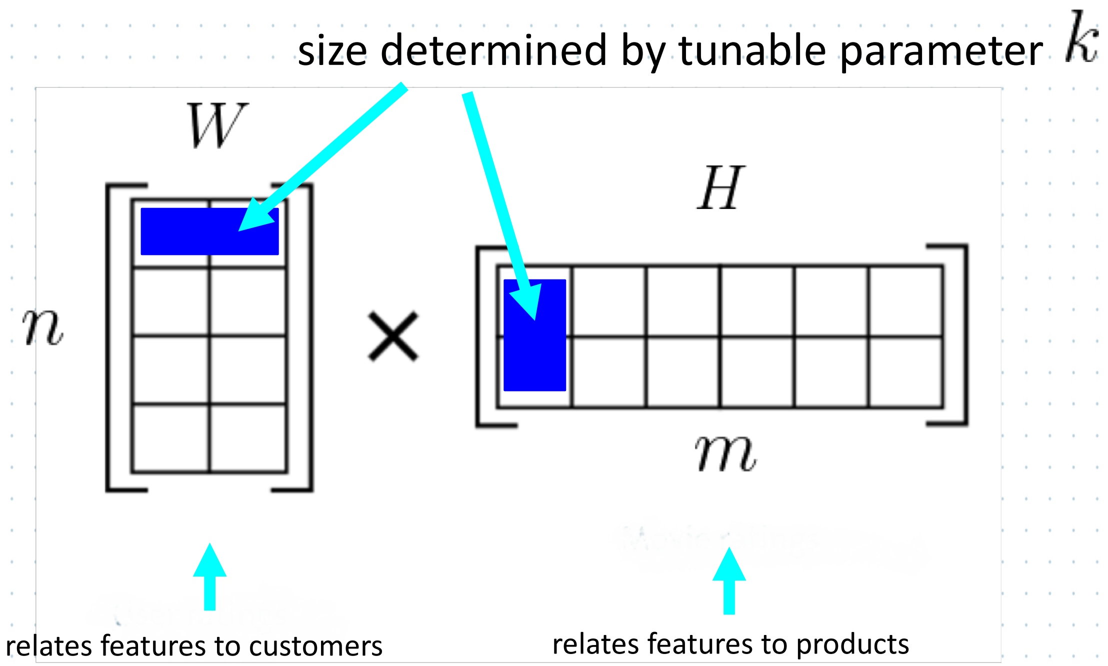


$$V = W \times H$$

minimise

$$\text{error} = V - (W \times H)$$

Nonnegative matrix factorization



How are ratings inferred?

We don’t only want to reconstruct, but also predict values.

Regularisation

- don’t want to learn exact representation of the training data
- regularisation terms “blur” the original data

Biases

- some customers buy only the minimum in accessories, others like to configure every detail
- some features are especially popular, others bought only rarely
- incorporate these biases in the data into predictions

Koren, Yehuda, Robert Bell, and Chris Volinsky. "Matrix factorization techniques for recommender systems." *Computer* 8 (2009): 30-37.

Regularisation

Add a regularisation term to the update rule:

$$\underset{W,H}{\arg\min} \sum_{i,j \in \kappa} \|V_{ij} - W_j^T H_i\|_2$$

$$\underset{W,H}{\arg\min} \sum_{i,j \in \kappa} \|V_{ij} - W_j^T H_i\|_2 + \lambda(\|W_j\|^2 + \|H_i\|^2)$$

non-zero entries of V

controls extent of regularisation

Koren, Yehuda, Robert Bell, and Chris Volinsky. "Matrix factorization techniques for recommender systems." *Computer* 8 (2009): 30-37.

Biases

Add aspects that are independent of any interaction between customers and products:

global bias, mean of all values in training data

$$V_{ij} = W_j^T H_i \quad \Rightarrow \quad V_{ij} = b + b_i + b_j + W_j^T H_i$$

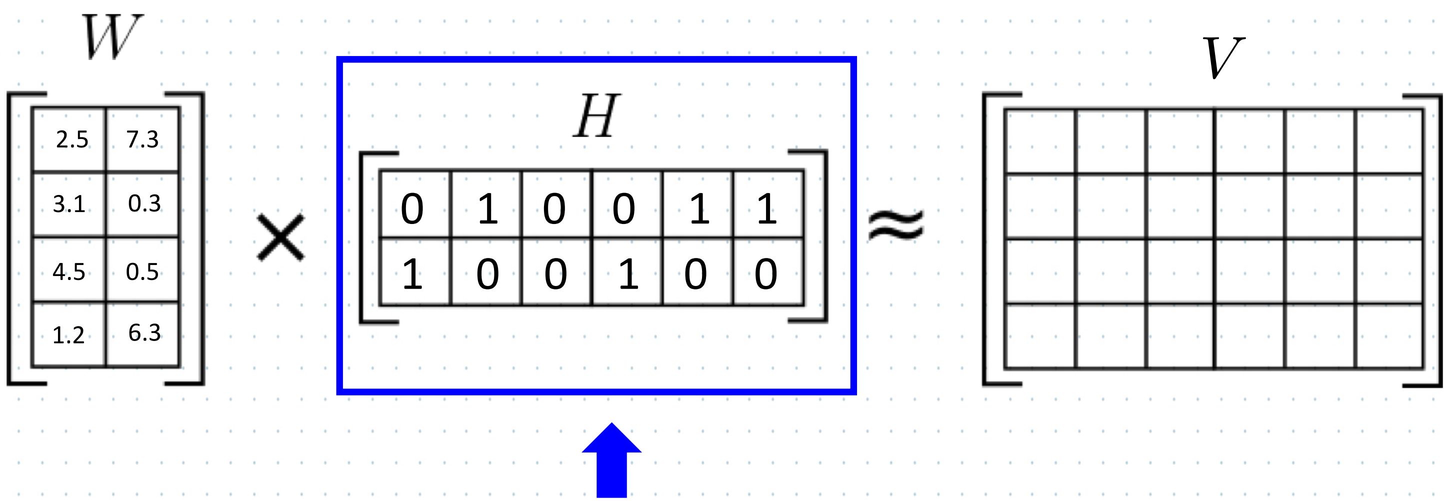
Learn additional value b_i for each customer and b_j for each product:

$$b_{i+1} = b_i + \alpha(\text{error} - \beta \cdot b_i)$$
$$b_{j+1} = b_j + \alpha(\text{error} - \beta \cdot b_j)$$

approximation error of prediction

Koren, Yehuda, Robert Bell, and Chris Volinsky. "Matrix factorization techniques for recommender systems." *Computer* 8 (2009): 30-37.

NBMF on D-Wave



We can put H in QUBO form by constraining it to binary values only and constructing a QUBO for each column.

O'Malley D, Vesselinov VV, Alexandrov BS, Alexandrov LB (2018) Nonnegative/Binary matrix factorization with a D-Wave quantum annealer. PLoS ONE 13(12): e0206653. https://doi.org/10.1371/journal.pone.0206653

Optimisation task on D-Wave

We want to optimise each column q of H such that

$$H_i = \underset{q \in \{0,1\}^{k \times m}}{\arg\min} \|V_i - Wq\|_2$$

turn into QUBO

$$f(q) = \sum_i a_i q_i + \sum_{i<j} b_{ij} q_i q_j$$

$$a_j = \sum_k W_{kj}(W_{kj} - 2V_{ij})$$

$$b_{jk} = 2\sum_l W_{lj} W_{lk}$$

O'Malley D, Vesselinov VV, Alexandrov BS, Alexandrov LB (2018) Nonnegative/Binary matrix factorization with a D-Wave quantum annealer. PLoS ONE 13(12): e0206653. https://doi.org/10.1371/journal.pone.0206653

Customer 994

Model: SEAT LEON CUPRA

Exterior colour: Urban Silver

Interior colour: Magic Black

Discount package

Rear view camera system

Dark tinted side windows

Power-adjustable heated and electric

SEAT FULL LINK

Convenience package rain light

Integrated maps SD card w/ Mapcare

Adaptive Cruise Control ACC

Navigation system

Driver assistance pack front camera

Interior LED light package

Family package curtains

DAB Digital Audio Broadcasting

Keyless locking and starting system

Safety package warning signal on front

Recommendation of an alternative color scheme:

Exterior colour: Desire Red
Interior colour: Rodium Gray

Customer 44

Model: SEAT LEON ST

Exterior colour: Desire Red

Interior colour: Deep Black

Discount package

Rear view camera system

Driver assistance pack front camera

SEAT FULL LINK

SEAT complete LED headlamps w/ sep LED

Adaptive Cruise Control ACC

Connectivity Box for navigation system

Digital instrument cluster

16-inch reduced spare wheel

Mapcare integrated maps update

Recommendation of additional accessory:

Air conditioning system

Conclusion

- POC hybrid recommendation system works
- run on larger dataset
- iterative algorithms take a long time to execute!

Thanks for your attention!