



A hybrid quantum-classical recommender system



POWERED BY VOLKSWAGEN GROUP

Andrea Skolik

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

The screenshot shows the Volkswagen configurator interface. On the left is a vertical navigation menu with icons and text: Volkswagen logo, Modelle (Cars), Finden & Kaufen (Find & Buy), Service & Zubehör (Service & Accessories), Elektromobilität (Electromobility), Impressum (Imprint), and Rechtliches (Legal). The main content area has a dark header with the text "Konfigurieren Sie Ihren Volkswagen." and two small icons. Below the header are eight car models arranged in two rows of four. Each model card includes a side-view image, the model name, a price range, a note about financing or lease, and a "Angebote" (Offers) button.

Model	Price Range	Notes	Offers
Der up!	ab 75,89 €/Monat *2, *3 oder 10.625,00 € *1		Angebote
Der Polo	ab 88,91 €/Monat *4, *3 oder 13.500,00 € *1		Angebote
Der neue T-Cross	ab 124,25 €/Monat *5, *3 oder 17.975,00 € *1		Angebote
Der Golf	ab 148,58 €/Monat *6, *3 oder 19.300,00 € *1		Angebote
Der T-Roc	ab 133,62 €/Monat *7, *3 oder 20.875,00 € *1		Angebote
Der Golf Sportsvan	ab 144,88 €/Monat *8, *3 oder 20.825,00 € *1		Angebote
Der Golf Variant	ab 162,67 €/Monat *9, *3 oder 22.200,00 € *1		Angebote
Der Touran	ab 187,64 €/Monat *10, *3 oder 24.975,00 € *1		Angebote

[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	0
1	0	1	...	1	1	1
2	0	0	...	0	0	1
3	0	0	...	0	0	1
4	0	0	...	1	1	0
5	1	0	...	1	1	1
6	0	0	...	0	0	0
7	1	0	...	0	0	0
8	0	1	...	1	1	1
9	0	0	...	1	1	1
10	1	0	...	1	1	1
11	0	0	...	0	0	0
12	1	1	...	0	0	0
13	1	0	...	1	1	1
14	1	0	...	0	0	0
15	1	0	...	0	0	1
16	0	0	...	1	0	0
17	0	0	...	1	1	1
18	0	1	...	1	0	0
19	1	0	...	1	1	1

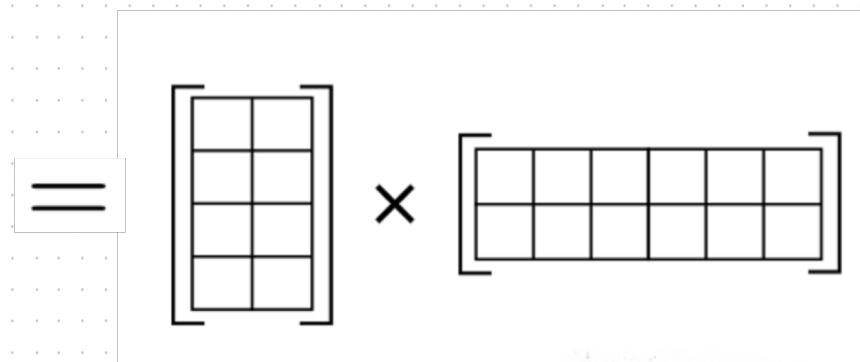
- data of 47819 car purchases
- data includes color packages, accessories, ...
- one-hot encoded categorical features
- turned them into “user ratings”
- 0: no purchase, 5: purchase

Nonnegative matrix factorization

m

n

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

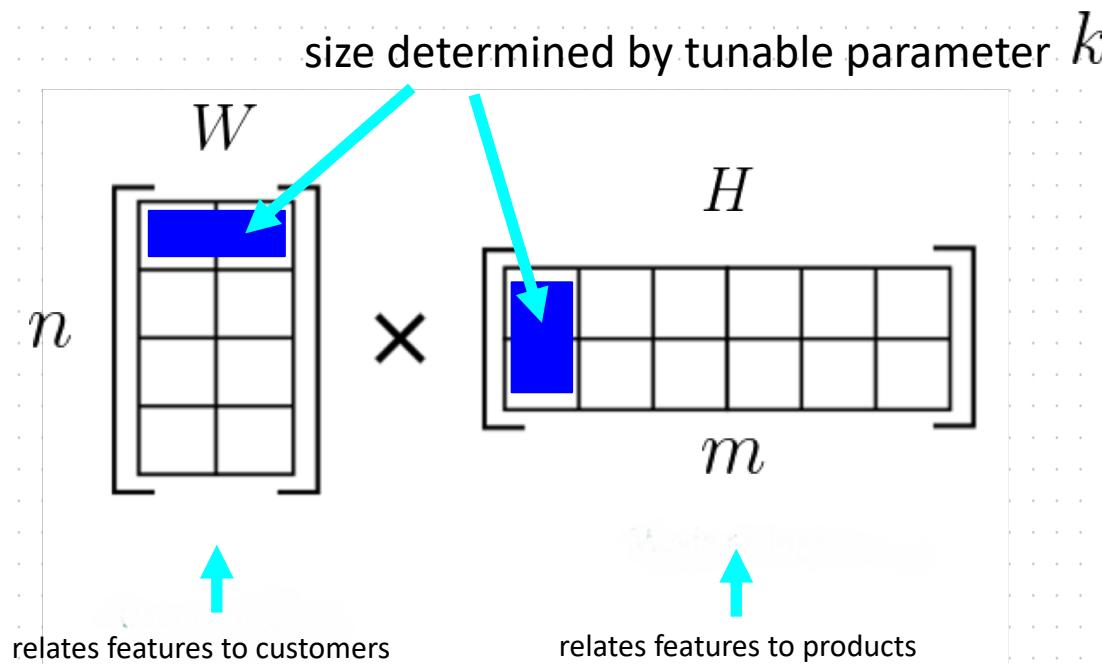


$$V = W \times H$$

minimise

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

Regularisation

Add a regularisation term to the update rule:

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



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



controls extent of regularisation

non-zero entries of V

Biases

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

global bias, mean of all values in training data

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

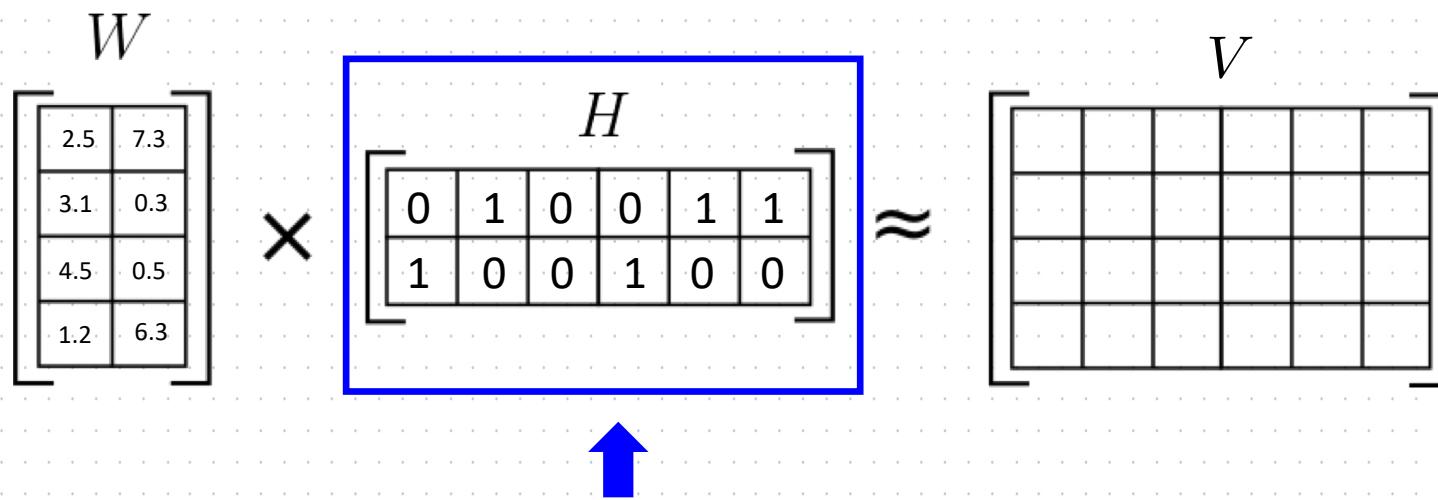
Learn additional value b_i for each customer and b_j for each product:

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

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

approximation error of prediction

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.

Optimisation task on D-Wave

We want to optimise each column q of H such that

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



turn into QUBO

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

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

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

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!