Insurance Quote Recommendations at Swiss Mobiliar Powered By In-Database ML

Thomas Baumann
Swiss Mobiliar
IBM Champion

Machine Learning Week Europe

November 19, 2024
Munich

1826

Formation

No. 1

for household contents, business, rental guarantee, legal protection and term life insurance

Our commitment

to research

UNIVERSITÄT BERN

Mobiliar Lab for Natural Hazards

ETH zürich

Mobiliar Lab for Analytics

UNI FR

Research cluster, University of Fribourg

Life and you

Insurance Quote Recommendationss

In-Database Machine Learning Use Case

die Mobiliar

0 Intro to In-Database ML

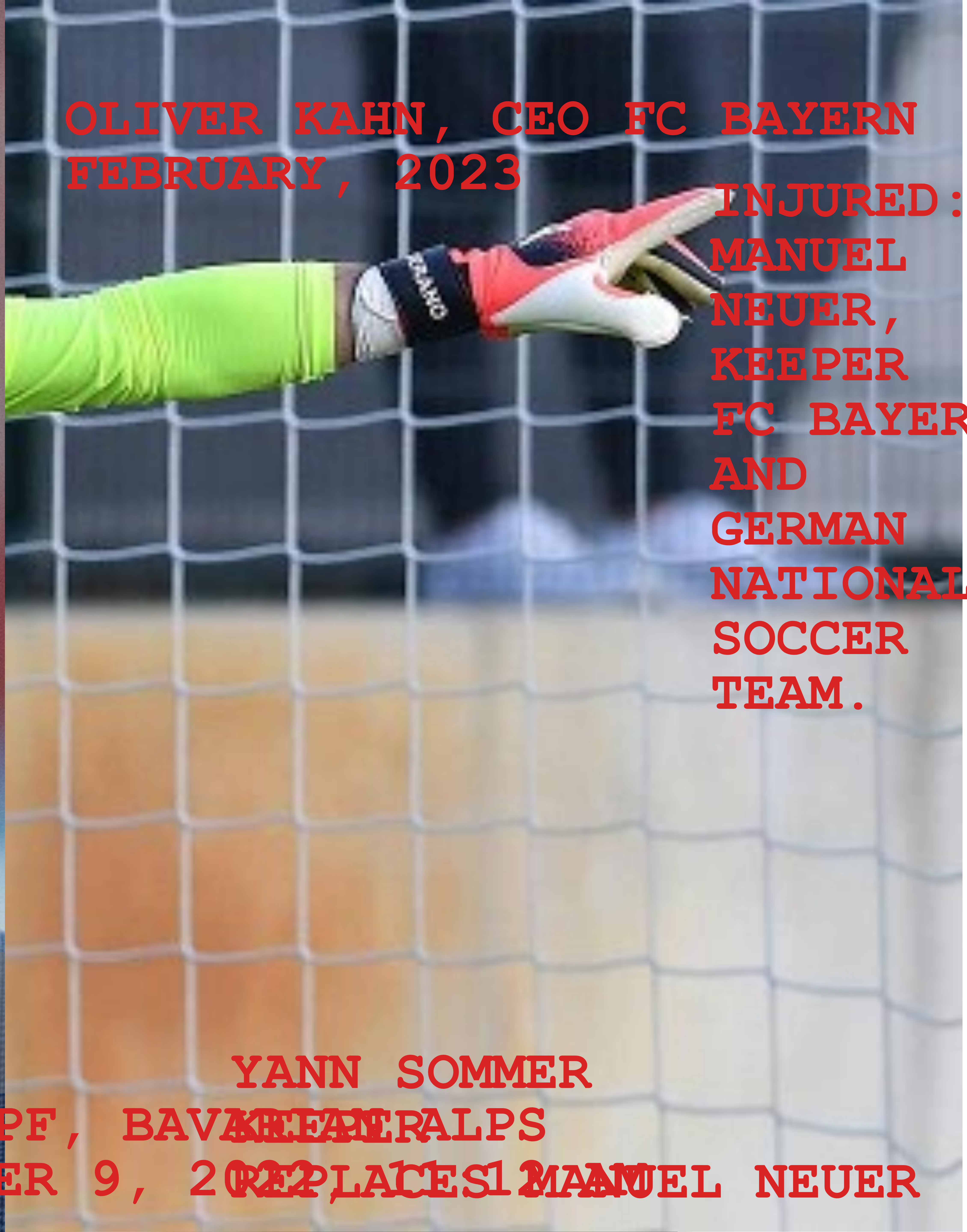
1 Swiss Mobiliar Use Case

2 In-Database ML Roadmap at Swiss Mobiliar

3 ML Explainability (Interpretability)

4 Summary


FC Bayern and the "tremendously difficult" search for a Neuer replacement
ran


OLIVER KAHN, CEO FC BAYERN
FEBRUARY, 2023
INJURED: MANUEL NEUER, KEEPER FC BAYERN AND GERMAN NATIONAL SOCCER TEAM.
YANN SOMMER
KEEPER
REPLACES MANUEL NEUER
ROSSKOPF, BAVARIAN ALPS
DECEMBER 9, 2022, 11 AM

In-Database Machine Learning

View "FIFA": 5k Rows, 42 attributes (40 to compare similarities)

NAME	NATIONALITY	OVERALL	POTENTIAL	WAGE_EUR	VALUE_EUR	AGE	HEIGHT_CM	WEIGHT_KG	ATTACKING_CROSSING	ATTACKING_FINISHING	ATTACKING_HEADING_ACCURACY	ATTACKING_SHORT_PASSING	ATTACKING_VOLLEYS	SKILL_DRIBBLING
Neymar Jr	Brazil	92	92	290000	105500000	27	175	68	87	87	62	87	87	96
L. Messi	Argentina	94	94	565000	95500000	32	170	72	88	95	70	92	88	97
K. Mbappe	France	89	95	155000	93500000	20	178	73	78	89	77	82	79	91
E. Hazard	Belgium	91	91	470000	90000000	28	175	74	81	84	61	89	83	95
K. De Bruyne	Belgium	91	91	370000	90000000	28	181	70	93	82	55	92	82	86
R. Burki	Switzerland	85	86	92000	32000000	28	187	85	15	8	17	37	13	12
M. Akanji	Switzerland	83	88	77000	31000000	23	187	91	53	36	79	80	42	69
X. Shaqiri	Switzerland	82	82	120000	23000000	27	169	72	79	71	45	82	76	86
G. Xhaka	Switzerland	81	84	94000	21500000	26	185	82	73	53	62	85	50	70
Y. Sommer	Switzerland	84	84	27000	21000000	30	183	79	13	13	10	40	8	15

SKILL_CURVE	SKILL_FK_ACCURACY	SKILL_LONG_PASSING	SKILL_BALL_CONTROL	MOVEMENT_ACCELERATION	MOVEMENT_SPRINT_SPEED	MOVEMENT_AGILITY	MOVEMENT_REACTIONS	MOVEMENT_BALANCE	POWER_SHOT_POWER	POWER_JUMPING
88	87	81	95	94	89	96	92	84	80	61
93	94	92	96	91	84	93	95	95	86	68
79	63	70	90	96	96	92	89	83	83	76
83	79	83	94	94	88	95	90	94	82	56
85	83	91	91	77	76	78	91	76	91	63
13	12	24	23	44	54	49	83	52	56	74
46	30	79	76	70	85	69	84	64	69	81
88	84	81	84	83	77	83	80	91	87	51
76	77	85	80	50	52	49	75	61	90	30
12	13	31	25	48	54	55	81	58	61	73

POWER_STAMINA	POWER_STRENGTH	POWER_LONG_SHOTS	MENTALITY_AGGRESSION	MENTALITY_INTERCEPTIONS	MENTALITY_POSITIONING	MENTALITY_VISION	MENTALITY_PENALTIES	MENTALITY_COMPOSURE	DEFENDING_MARKING	DEFENDING_STANDING_TACKLE
81	49	84	51	36	87	90	90	94	27	26
75	68	94	48	40	94	94	75	96	33	37
84	76	79	62	38	89	80	70	84	34	34
84	63	80	54	41	87	89	88	91	34	27
89	74	90	76	61	88	94	79	91	68	58
36	74	14	35	18	10	50	20	58	11	13
74	84	48	76	81	33	67	40	80	84	84
73	71	84	61	55	74	81	65	82	35	49
79	77	79	92	71	75	82	63	74	66	72
						58	24	57	9	19

GOALKEEPING_DIVING	GOALKEEPING_HANDLING	GOALKEEPING_KICKING	GOALKEEPING_POSITIONING	GOALKEEPING_REFLEXES
9	9	15	15	11
6	11	15	14	8
13	5	7	11	6
11	12	6	8	8
15	13	5	10	13
86	80	74	83	89
10	9	13	6	9
13	12	12	11	11
7	8	11	7	13
79	85	81	80	87

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In-Database Machine Learning


```
SELECT name, nationality
, AI_SIMILARITY(Name,'M. Neuer')
  as SIMILARITY_SCORE
FROM FIFA
ORDER BY 3 DESC
fetch first 30 rows only
```

	NAME	NATIONALITY	SIMILARITY_SCORE
	B. Leno	Germany	0.885024038046783
2	Ederson	Brazil	0.882723770502872
3	De Gea	Spain	0.880496660094689
4	Neto	Brazil	0.878024048672472
5	S. Handanovic	Slovenia	0.87800419338633
6	K. Navas	Costa Rica	0.877424840661706
7	J. Pickford	England	0.8768829530547
8	K. Schmeichel	Denmark	0.876774869105394
9	W. Szczesny	Poland	0.87579275272194
10	Alisson	Brazil	0.872326521849975
11	A. Areola	France	0.864849126946127
12	Rui Patricio	Portugal	0.864432105246983
13	R. Burki	Switzerland	0.862906215105855
14	H. Lloris	France	0.857519723142511
15	T. Courtois	Belgium	0.857407583420072
16	J. Cillessen	Netherlands	0.856265028773428
17	S. Romero	Argentina	0.854190859014894
18	A. Lopes	Portugal	0.851624479901499
19	Kepa	Spain	0.850749281904455
20	S. Ruffier	France	0.849047729799482
21	M. ter Stegen	Germany	0.847547588754877
22	P. Gulacsi	Hungary	0.843870876775031
23	Y. Sommer	Switzerland	0.842908851168139
24	S. Sirigu	Italy	0.837950177094316
25	Adan	Spain	0.83733394531309
26	M. Ryan	Australia	0.835842156630129
27	Sergio Asenjo	Spain	0.835608704126328
28	G. Donnarumma	Italy	0.832724353541428
29	A. Onana	Cameroon	0.831862366263634
30	M. Perin	Italy	0.831681990128982

```
SELECT
AI_FIFA_PREDICT(new player)as
VALUE_EUR
FROM SYSIBM.SYSDUMMY1
```

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Paradigm: Move the Algorithm, Not the Data

SDI (SQL Data Insights)* in a Nutshell

4 hours from idea to production

Step1: Select view to enable AI

Step2: Enable view for AI
- Triggers model creation ("training")
- Comparable to index creation

Step3: Fire semantic queries
- AI_SIMILARITY (find similar rows)
- AI_SEMANTIC_CLUSTER (similar rows compared to max 3 rows)
- AI_ANALOGY (find analogies between pairs of rows)
- AI_COMMONALITY (find uncommon rows)

Frictionless AI

No data scientists involved
- One size fits all model (neural net)

No data scientist framework necessary
- Models stored and maintained in catalog

No data lift and shift necessary
- Analyze data where it lives

* IBM Db2's implementation of In-Database ML is called *SQL Data Insights* (SDI). Oracle calls it *Oracle Machine Learning*.

Db2 SQL Data Insights: Unsupervised Neural Network Approach for Natural Language Processing

NAME	NATIONALITY	OVERALL	POTENTIAL	WAGE_EUR	VALUE_EUR	AGE	HEIGHT_CM	WEIGHT_KG	ATTACKING_CROSSING
M. Neuer	Germany	88	88	155000	32000000	33	193	92	15
Y. Sommer	Switzerland	84	84	37000	21000000	30	183	79	13

Each field (column of a row in a view) is converted to a text token. Columns to be classified as numerical or categorical by user before training starts.

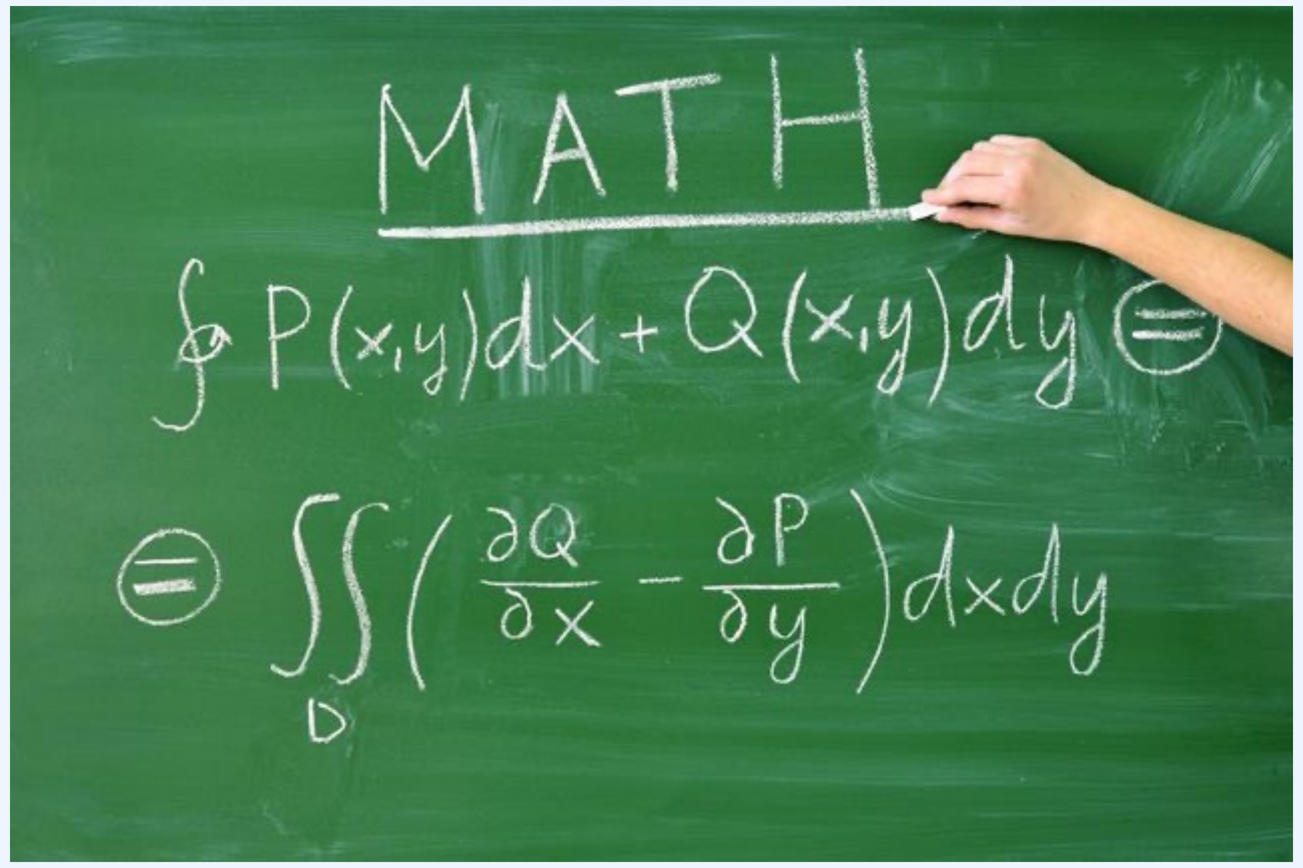
Each row of a view is considered as an unordered English-like sentence (bag-of-words) of text tokens.

Generates semantic representations of words using vectors (vector embedding).

Semantic similarities between words measured using distance between vectors.

Swiss Mobiliar Use Case: Success Prediction for Vehicle Insurance Quotes

P(contract will be signed)=?



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1

We compare 24 attributes for similarity search.

2

We scan 15 million rows of quote data.

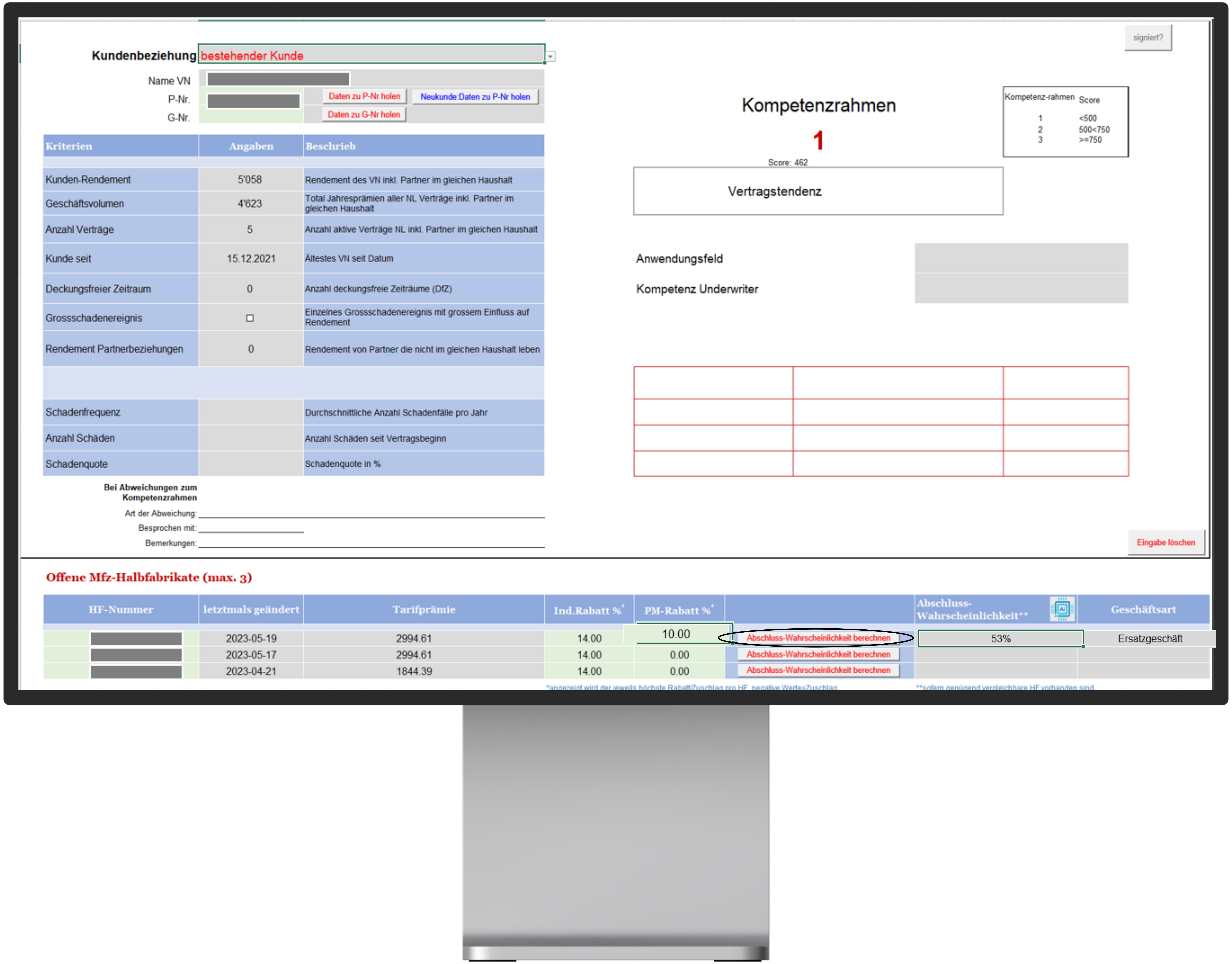
3

We search the 43 most similar quotes of the past.

4

We calculate their average success factor.

App
Screen Shot



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Swiss Mobiliar
Use Case Based
on 24 Attributes

10 attr

with customer data

Year of birth, Gender and Nationality of customer and of most frequent driver, Customer loyalty, Licence withdrawn > 3 month, Bonus/malus rate

5 attr

with vehicle data

Year of putting into circulation, Year of purchase,
Leasing, Type of use,
List price, Accessories

9 attr

with offer data

Individual and Product Management (PM) discounts (%), Premium, Deductibles for Collision, Theft, Glass breakage, Liability, Parking damage and Young drivers

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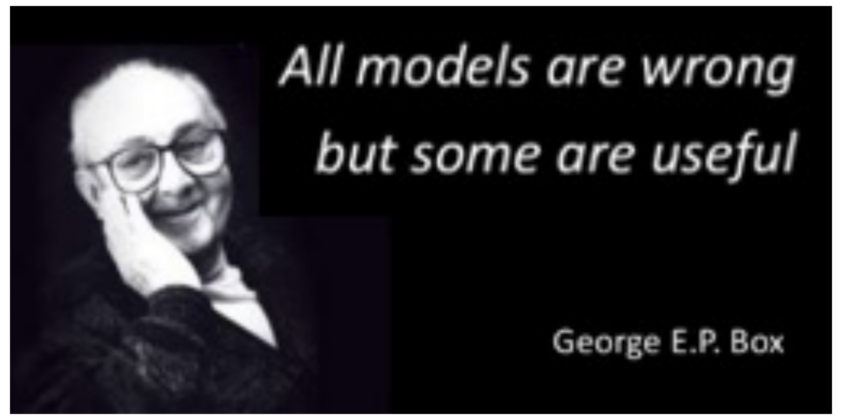
KPI of Success Prediction Use Case

Is the model useful as such?



Calculate accuracy * and other model KPI

90+%

*True Positive (TP):
Prediction >= 50% and quote converted
True Negative (TN):
Prediction < 50% and quote not converted
Accuracy = (TP+TN) / all

Do we have enough resources for training?

Must fit into scheduled resource planning

20min 1M keys

Is the scoring process fast enough?

Scoring time must be below 3sec

<2sec dividing[2]

[2]: Data partitioning into pieces of 2 Mio unique keys / view

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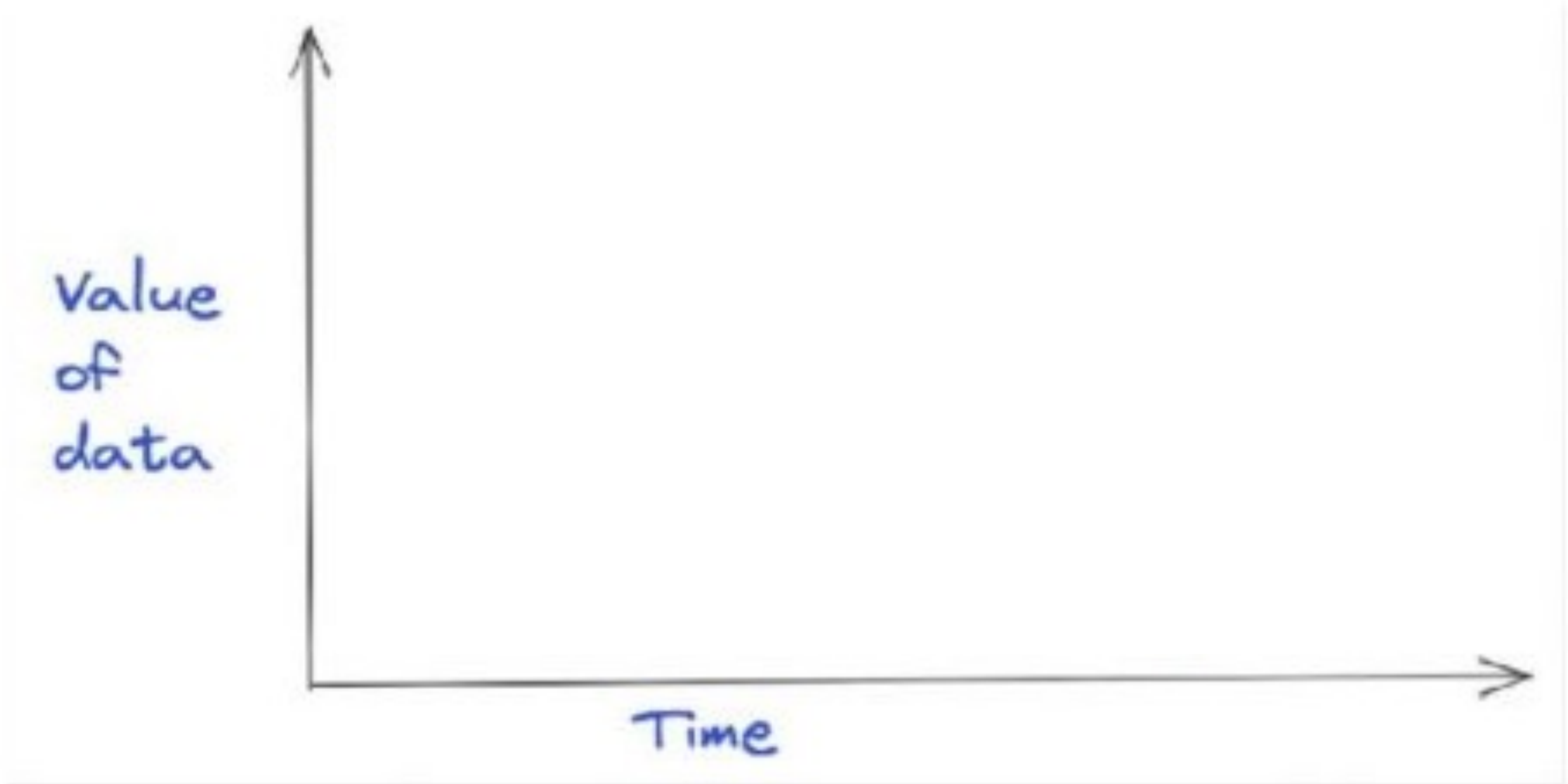
Move the Algorithm, Not the Data
Sweet Spots for In-Database ML to Identify Use Cases



Analyze data even if it's not yet committed.

Insert missing values, identify outliers.

Whenever the value of data over time decreases significantly, ML on data where it lives becomes important.

Avoid Data Lift and Shift:

- Why should I encrypt my data in a database and monitor each individual access when there are several more copies out there?
- I do not want to lose control of my data, e.g. if a customer requests the deletion of their data or if the law requires the deletion of old data.

Swiss Mobiliar In-Database ML Roadmap

Dec 2022 to Spring 2023

From PoC to production with AI_SIMILARITY() for vehicle offers

Fall 2023

AI_SIMILARITY() for other products

Spring 2024

AI_SIMILARITY() for other use cases.

Predict household inventory sum based on location (zip code), YOB, no of rooms

Summer 2024

Outlier Detection (AI_COMMONALITY)

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Agenda

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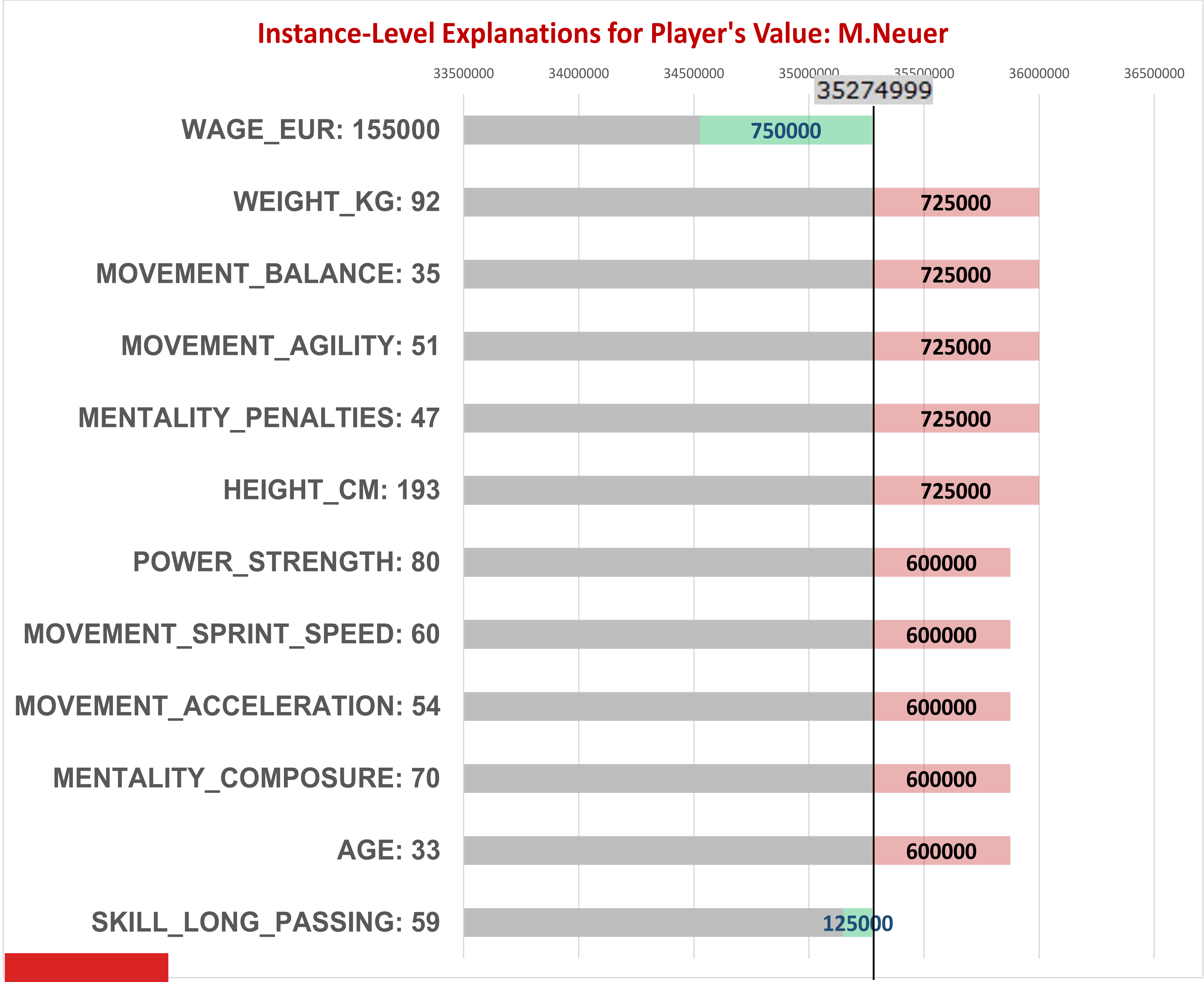
Explain the Model (2 | 2):
How much does each attribute contribute?



How to read:

"If we add the attribute WAGE_EUR to the model, the predicted value increases by $750,000 ."

"If we add weight_kg to the model, the predicted value decreases by $725,000 ."

```
SELECT
AI_FIFA_PREDICT('M. Neuer')
as VALUE_EUR
FROM SYSIBM.SYSDUMMY1
```

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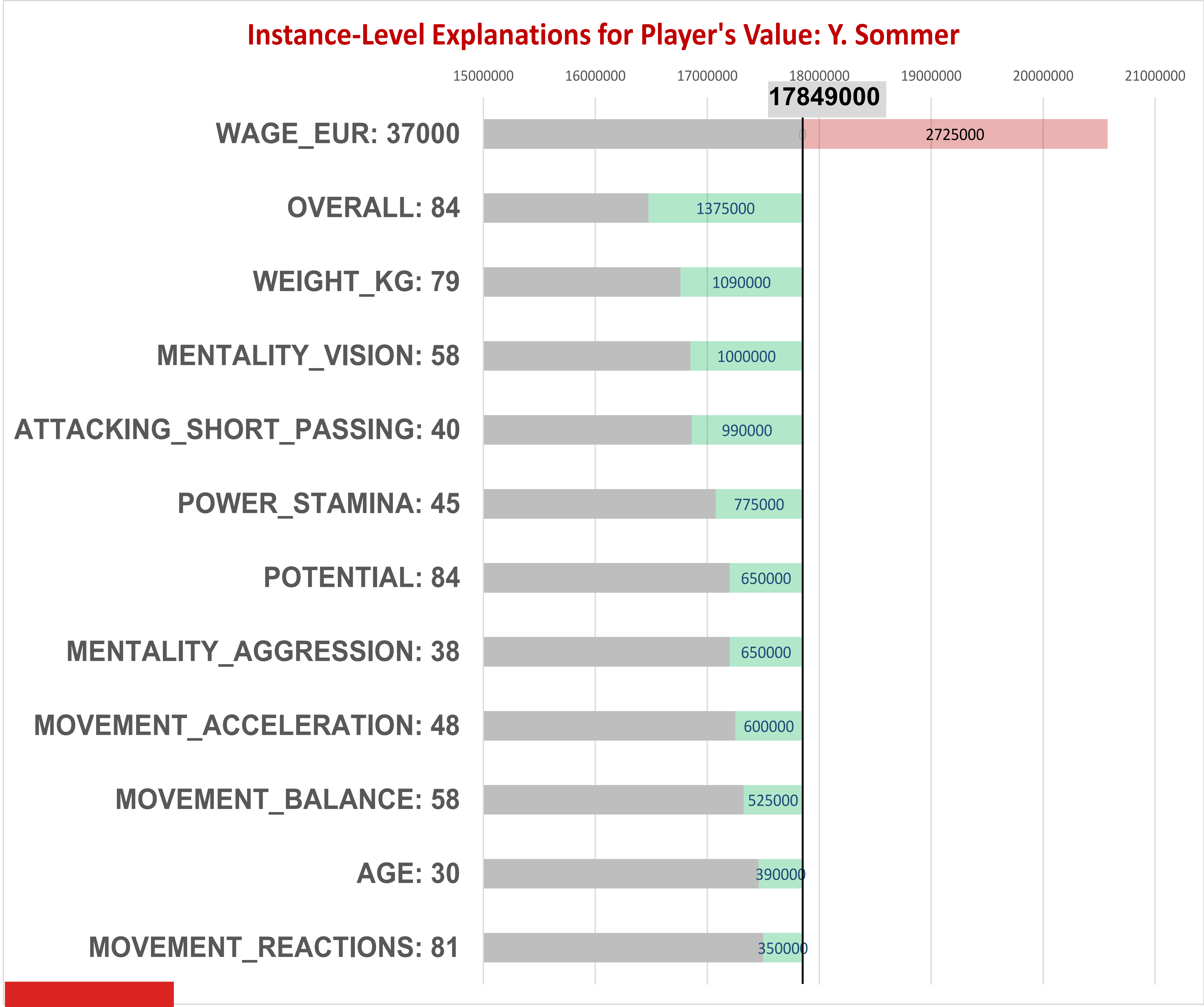
Explain the Model (2 | 2):
How much does each attribute contribute?



How to read:

"If we add the attribute WAGE_EUR to the model, the predicted value decreases by $2,725,000 ."

"If we add weight_kg to the model, the predicted value increases by $1,090,000 ."

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4 hrs

ideation to production

<2sec

response time

15 m

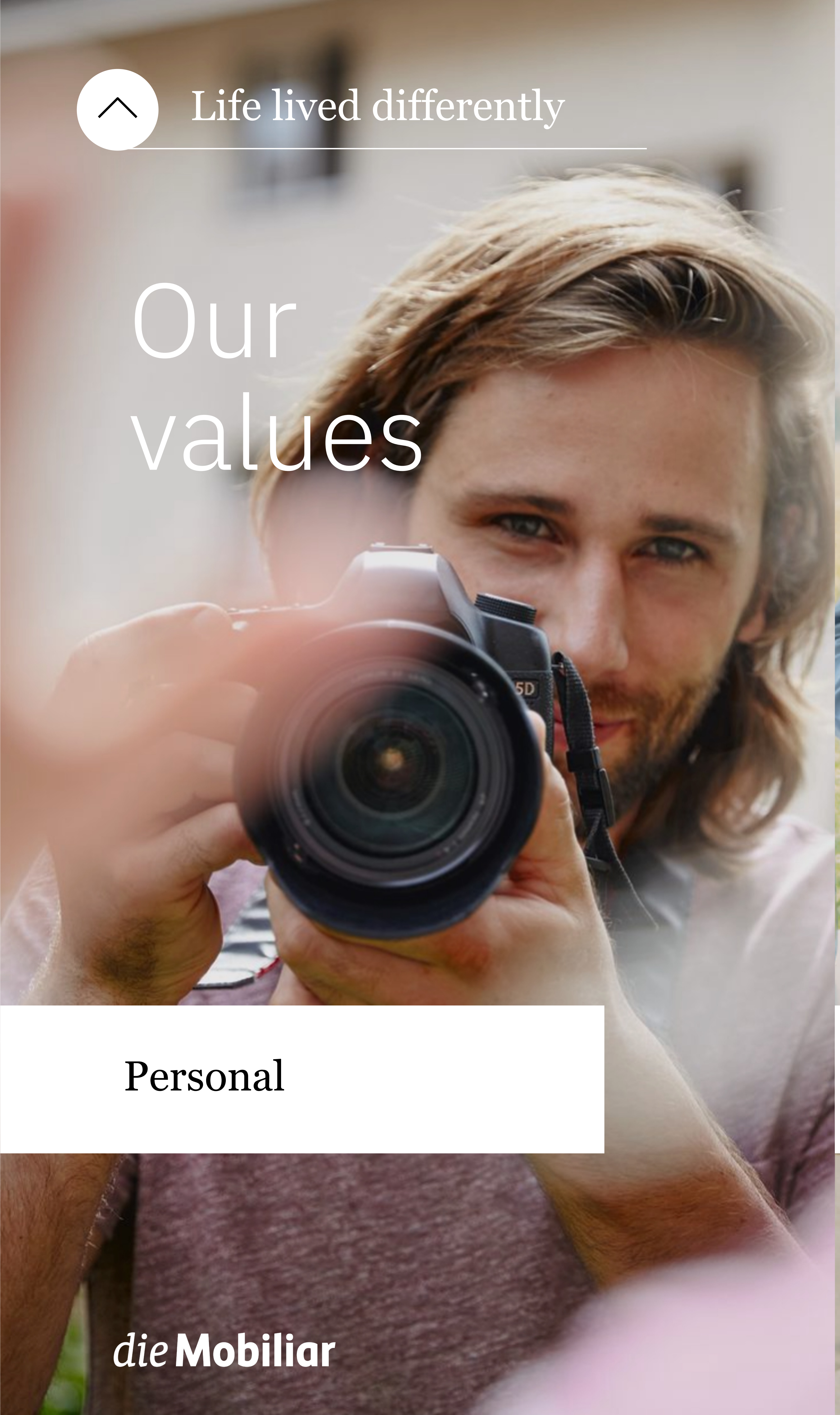
data records processed

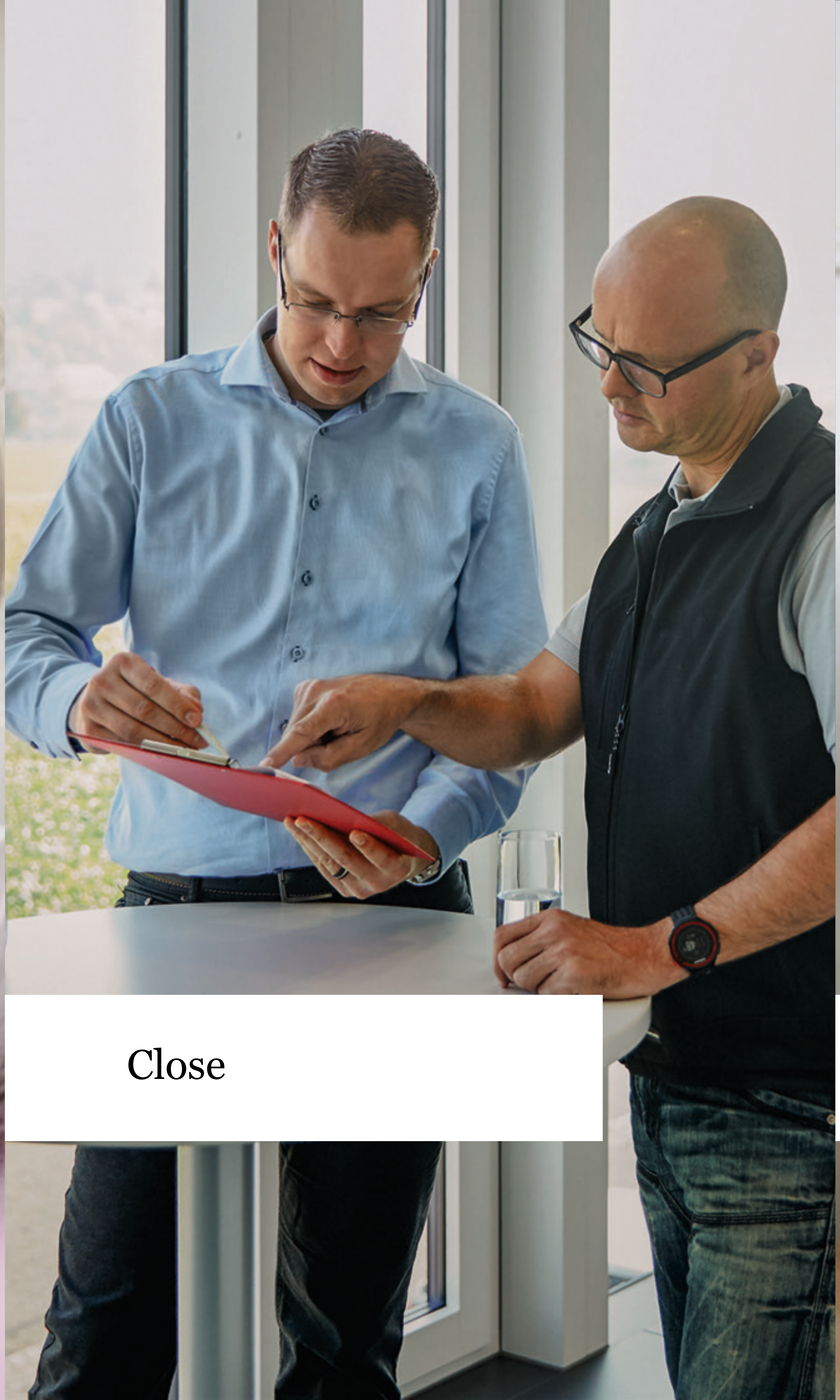
90% +

success rate

Life lived differently

Our values





Q&A

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