

“AI or not AI”

AI Use Cases and Anti-Patterns

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AI
AI

Problem #1







Problem #2







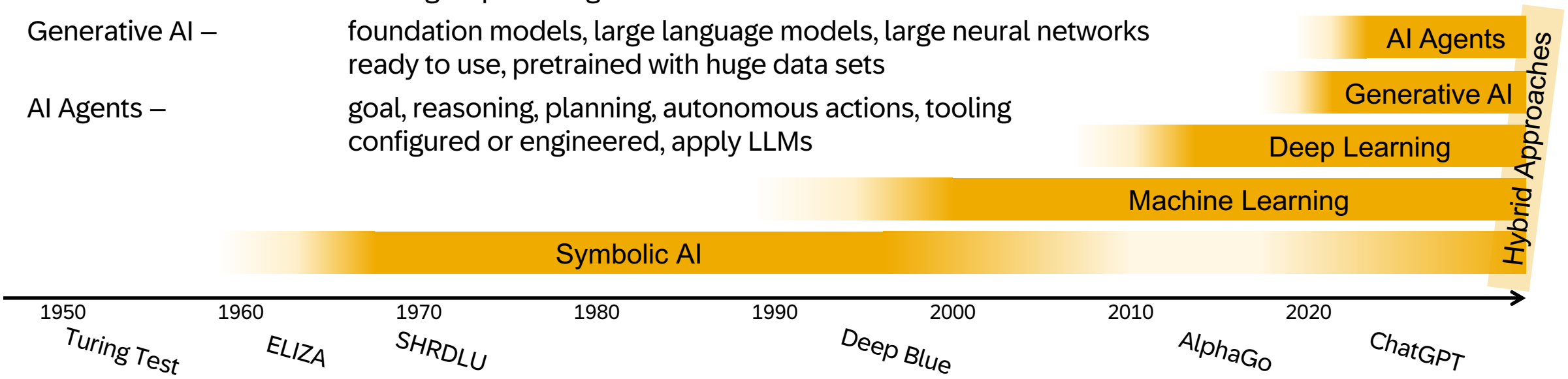

TRADITIONAL SOFTWARE
Reliable. Proven.
The foundation
of everything.
FOUNDATION


MACHINE LEARNING
& GENERATIVE AI
New powerful tools
amplify what's possible.
TRADITIONAL
SOFTWARE
Reliable. Proven.
The foundation
of everything.
POWER
POWER
FOUNDATION


AGENTIC ENGINEERING
The agent orchestrates, plans, adapts and uses all tools to achieve complex goals.
GOAL PLANNING
TASK BREAKDOWN
AI
AGENT
AUTONOMOUS
INTELLIGENT
ADAPTIVE
REASONING
ADAPTATION
TOOL USE
MACHINE LEARNING & GENERATIVE AI
New powerful tools amplify what's possible.
POWER
TRADITIONAL SOFTWARE
Reliable. Proven. The foundation of everything.
FOUNDATION
Not everything that's lame is an analogy.

Artificial Intelligence – Technology Evolution

Symbolic AI –	knowledge representation, logic, search, heuristics, expert systems engineered by developers
Machine Learning –	statistical learning from data, supervised or unsupervised data scientists in the lead
Deep Learning –	large neural networks, speech, vision training requires large data sets
Generative AI –	foundation models, large language models, large neural networks ready to use, pretrained with huge data sets
AI Agents –	goal, reasoning, planning, autonomous actions, tooling configured or engineered, apply LLMs





AI or not AI?

The more reasonable questions are:

- What is the **nature** of my problem?
- What is the **right approach** to solve my problem?
- **Can AI help** and play a role in it?
- Which AI **tools** are helpful for my use case? If any…
- How can they be **combined**?
- Do I have the necessary **prerequisites**?
- Which problems or pitfalls can break the approach?

➔ Start with the use case and look for the right tool (set)



Symbolic AI
Use Cases & Patterns

Symbolic AI – Use Cases

Optimization in logistics, manufacturing and supply chain

Time tabling, workforce allocation, resource scheduling

Deterministic games like chess engines or logic puzzles

Industrial troubleshooting with clear causal rules (aka Expert Systems

Common Pattern:

- Clear and precisely codifiable rules
- Guarantee of correctness required
- Transparency / explainability is key
- No generalization from data required

➔ Symbolic AI – incl. search and optimization methods

Symbolic AI - Anti-Patterns and Pitfalls



Need to find a proper representation of the problem

Perfect algorithms are often NP complete (not running in reasonable time on relevant data)

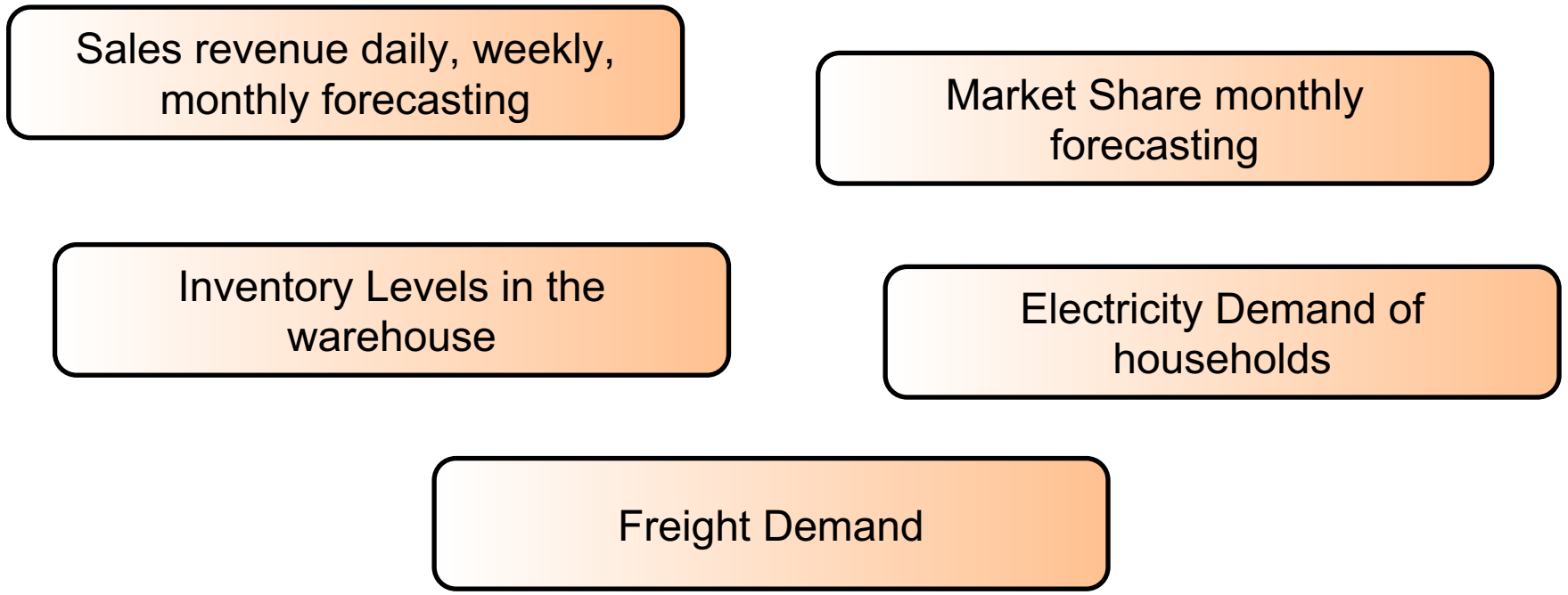
Heuristics applied to reduce runtime – depend on programmers' "intelligence"

No consideration of the underlying data



Machine Learning
Use Case & Patterns

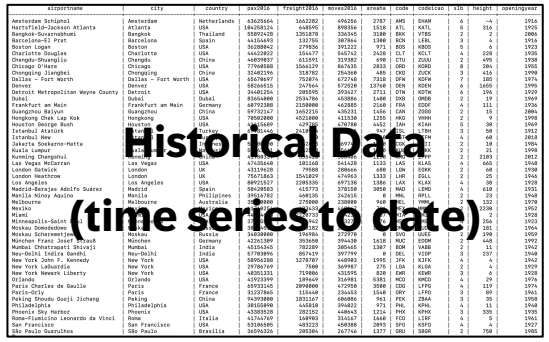
Time Series Forecasting Pattern – Customer Use Cases

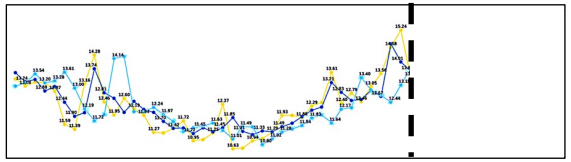


Common Pattern:

- Customer is analyzing historical data and wants to get a forecast into the future
- Machine Learning helps to extrapolate the historical data (time series) into the future

Machine Learning Basics – Time Series Forecasting





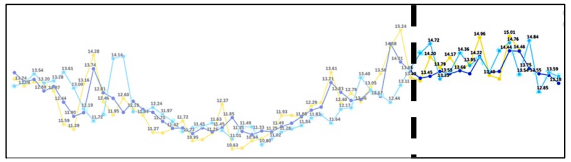
Historical Data (time series to date)

Train and Test your own Model

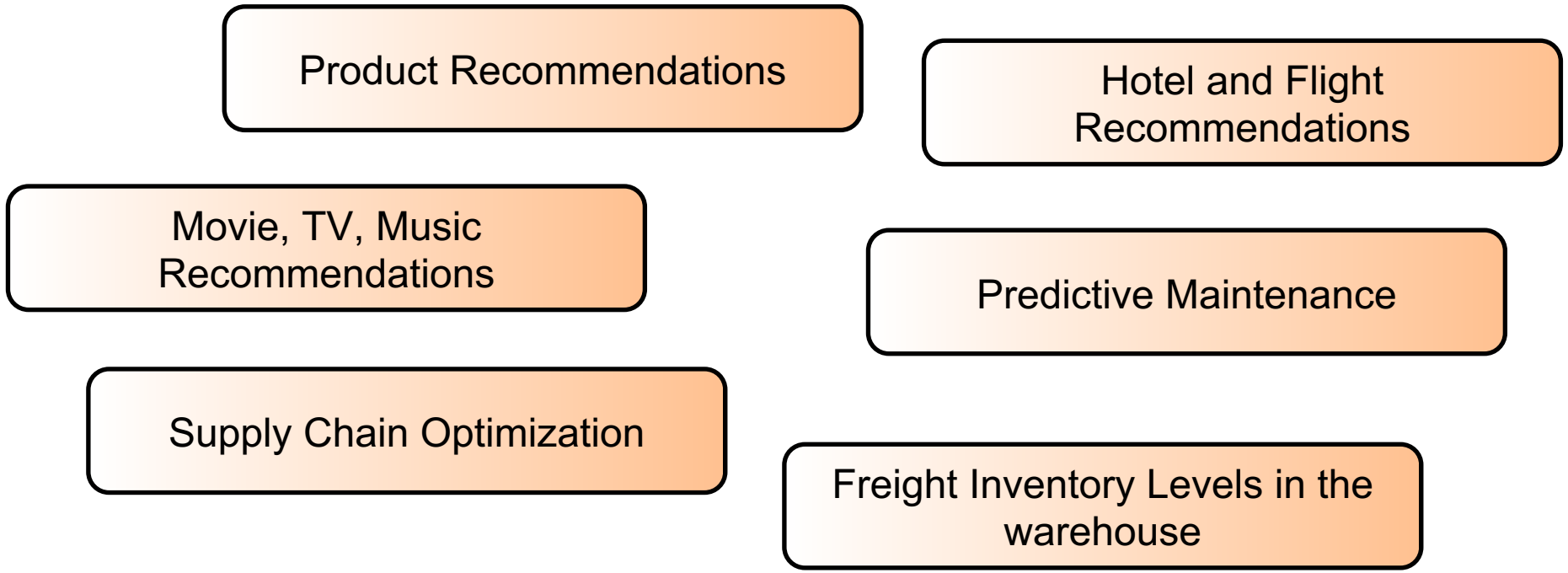
Input: 3 months

Your Own ML Model

Output: Forecast (future data)



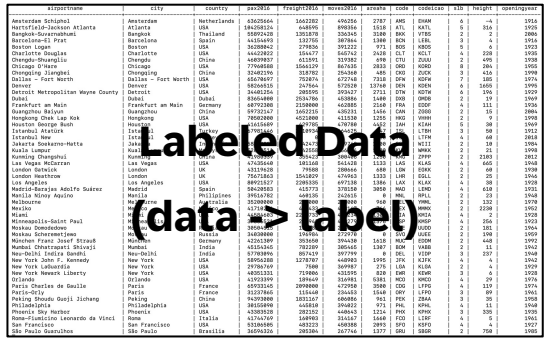
Recommendations Pattern – Customer Use Cases



Common Pattern:

- Based on existing data, recommendations are wanted
- Machine Learning calculates the recommendations based on the collected historical data

Machine Learning Basics – Recommendations and Classifications



airportname	city	country	pax2016	freight2016	moves2016	avnaha	code	codeicao	x1b	height	openingyear
Amsterdam Schiphol	Amsterdam	Netherlands	63635664	1662282	496256	2787	AMS	EHAM	6	-4	1916
Hartsfield-Jackson Atlanta	Atlanta	USA	104250124	448695	890364	1618	ATL	KATL	6	316	1926
Bangkok-Suvarnabhumi	Bangkok	Thailand	55892428	1351870	336345	3180	BKK	VTBS	2	2	2006
Barcelona-El Prat	Barcelona	Spain	44354499	132755	387844	1380	BCN	LEBL	3	4	1916
Boston Logan	Boston	USA	36288842	279836	391222	971	BOS	KBOS	5	6	1923
Charlotte Douglas	Charlotte	USA	44423922	154477	560742	2428	CLT	KCLT	4	228	1935
Chengdu-Shuangliu	Chengdu	China	44899837	611591	319382	690	CTU	ZUUU	2	495	1938
Chicago O'Hare	Chicago	USA	79848286	1844325	867468	1800	ORD	KORD	8	668	1955
Chongqing Jiangbei	Chongqing	China	21483196	302197	161569	485	CKG	ZUCK	3	414	1990
Dallas - Fort Worth	Dallas - Fort Worth	USA	65678697	713674	672748	7318	DFW	KDFW	7	185	1974
Denver	Denver	USA	58264535	2a76aa	572528	13748	DEN	KDEN	6	1605	1995
Detroit Metropolitan Wayne County	Detroit	USA	34481256	205595	393427	2711	DTW	KDTW	6	196	1929
Dubai	Dubai	Dubai	83664490	3534a7e	452886	1a00	DXB	OMDB	2	19	1969
Frankfurt am Main	Frankfurt am Main	Germany	60792380	2150000	462885	2160	FRA	EDDF	4	111	1936
Guangzhou Baiyun	Guangzhou	China	69732147	1602235	438231	1a6a	CAN	ZGGG	2	15	2004
Hongkong Chek Lap Kok	Hongkong	USA	70502000	4521000	411530	1255	HKG	VHHH	2	9	1998
Houston George Bush	Houston	USA	41616499	297700	479780	ga32	IAH	KIAH	5	98	1969
Istanbul Atatürk	Istanbul	Turkey	61632774	1189362	469525	2a00	ISL	LTBA	3	50	1912
Istanbul New	Istanbul							LTFM	4	60	2018
Jakarta Soekarno-Hatta	Jakarta							WIII	2	10	1984
Kuala Lumpur	Kuala Lumpur							WMKK	2	69	1998
Kunming Changshui	Kunming	China	46412281	2a4c2e	254a18	1a8a	KMG	ZPPP	2	2161	1012
Las Vegas McCarran	Las Vegas	USA	47435640	181648	541428	1133	LAS	KLAS	4	665	1948
London Gatwick	London	UK	43119428	79500	280646	680	LGW	EGKK	2	60	1958
London Heathrow	London	UK	75671863	1541029	474963	1333	LHR	EGLL	2	25	1946
Los Angeles	Los Angeles	USA	84921527	2206336	697128	1386	LAX	KLAX	4	38	1928
Madrid-Barajas Adolfo Suárez	Madrid	Spain	50420503	415773	378158	3050	MAD	LEMD	4	610	1931
Manila Ninoy Aquino	Manila	Philippines	39514702	449135	242615	0	MNL	RPLL	2	23	1948
Melbourne	Melbourne	Australia	35200800	2	2	960	YMML	YMML	2	132	1970
Mexico	Mexico							MMMX	2	2230	1902
Miami	Miami							KMIA	4	2	1928
Minneapolis-Saint Paul	Minneapolis							KMSP	4	256	1923
Moskau Domodedowo	Moskau							UUDD	2	181	1964
Moskau Scheremetjewo	Moskau	Russia	36504400	194764	372078	0	SVO	UUEE	2	192	1959
München Franz Josef Strauß	München	Germany	42352190	3034450	395438	1418	MUC	EDDM	2	448	1992
Mumbai Chhatrapati Shivaji	Mumbai	India	42154345	702209	395465	1307	BOM	VABB	2	11	1942
Neu-Delhi Indira Gandhi	Neu-Delhi	India	57783096	867419	397799	0	DEL	VIDP	3	237	1968
New York John F. Kennedy	New York	USA	58056288	1278707	448903	1995	JFK	KJFK	4	4	1942
New York Laguardia	New York	USA	29784749	7600	369987	275	LGA	KLGA	2	4	1929
New York Newark Liberty	New York	USA	40351331	719066	431595	820	EWR	KEWR	3	6	1928
Orlando	Orlando	USA	41953399	189649	314981	5381	MCO	KMCO	4	29	1976
Paris Charles de Gaulle	Paris	France	65933145	2090000	472958	3580	CDG	LFPG	4	119	1974
Paris-Orly	Paris	France	31237845	115448	234453	1548	ORY	LFPO	3	89	1961
Peking Shoudu Guoji Jichang	Peking	China	94393880	1031167	608886	961	PEK	ZBAA	3	35	1958
Philadelphia	Philadelphia	USA	38150490	448848	394022	971	PHL	KPHL	4	11	1940
Phoenix Sky Harbor	Phoenix	USA	43303528	282152	440643	1214	PHX	KPHX	3	335	1935
Rome-Fiumicino Leonardo da Vinci	Rome	Italia	41744749	149753	434167	1648	FCO	LIRF	4	4	1961
San Francisco	San Francisco	USA	51304385	465224	443968	2093	SFO	KSFO	4	13	1927
São Paulo Guarulhos	São Paulo	Brasilia	34694336	208384	267746	1377	GRU	SBGR	2	750	1985

Labeled Data (data -> label)

Train and Test your own Model

Input: data

Your Own ML Model

Output: Label (Recommendation or Class)

Machine Learning - Anti-Patterns and Pitfalls



Not sufficient historical data, esp. for forecasting

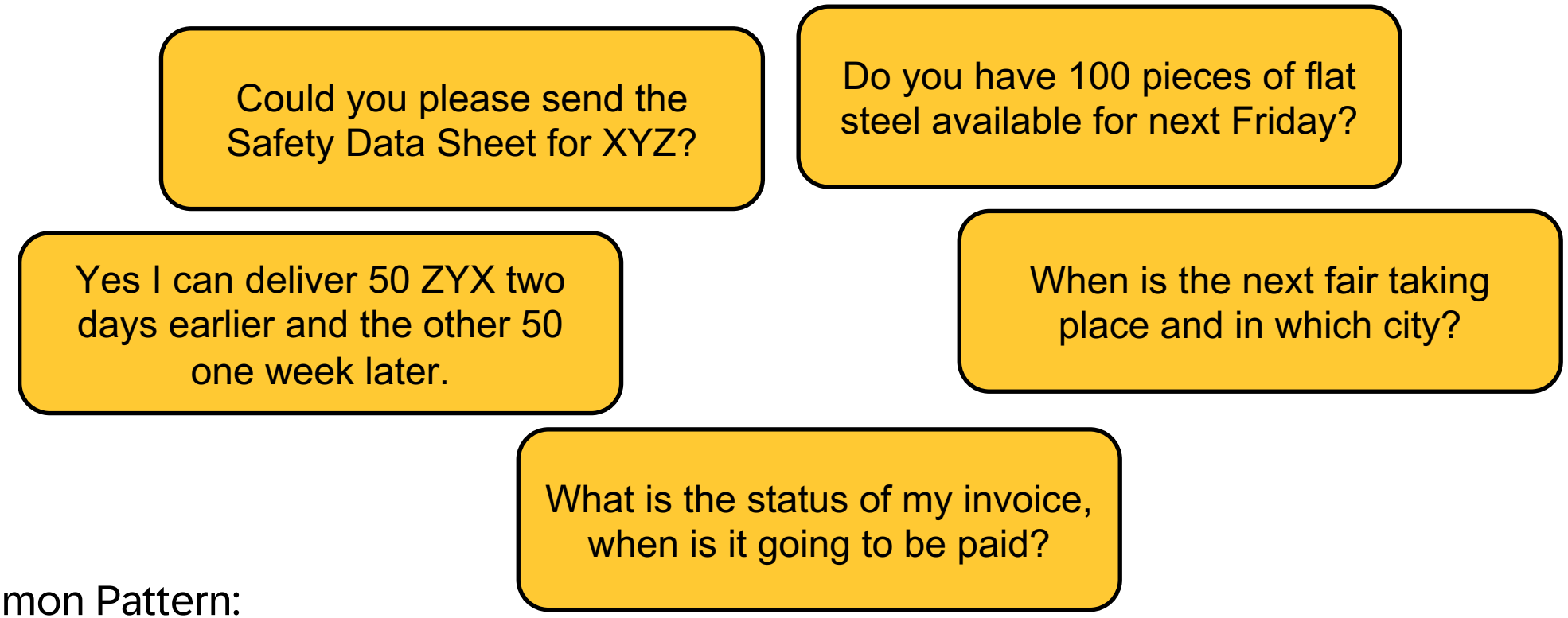
Data can be limited in scope or even be biased

Correlation does not imply causation
(https://www.tylervigen.com/spurious-correlations)



Generative AI
Use Case & Patterns

Incoming Messages Pattern – Customer Use Cases



Common Pattern:

- Large amount of very similar incoming messages seeking for a response. Response mostly needs a lookup in one or multiple systems.
- Generative AI helps to analyze, categorize, extract information out of the message in order to process the request in the system and generate a response.

GenAI Basics – Information Extraction

I received the following mail:

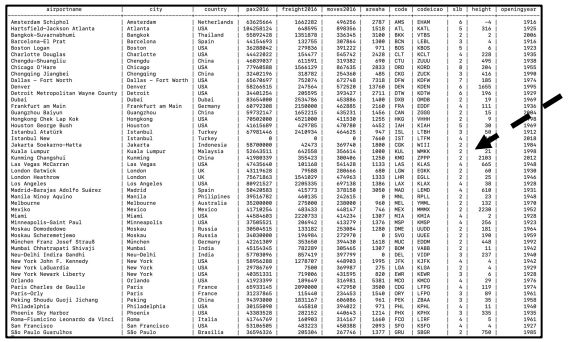
“Hi, I need to cancel my reservation no DZ345YZ … to … at … please advice, best John”

Analyze and extract:
- **snd**: sender of the mail
- **res**: reservation number
- **trd**: travel date
- **ctr**: country to travel to
- **sum**: summary in 10 words max

Return a nice JSON structure …




```
{
   "snd": "John Doe",
   "res": "DZ345YZ",
   "trd": "10-10-2024",
   "ctr": "Germany",
   "sum": "John wants to
      cancel his travel”
}
```



airportname	city	country	pax2016	freight2016	moves2016	areaha	code	codeicao	alt	height	openingyear
Amsterdam Schiphol	Amsterdam	Netherlands	63625664	1662282	496256	2787	AMS	EHAM	6	-4	1916
Hartsfield-Jackson Atlanta	Atlanta	USA	104250124	646596	890936	1618	ATL	KATL	5	316	1926
Bangkok-Suvarnabhumi	Bangkok	Thailand	55092428	1351878	336345	3100	BKK	VTBS	2	2	2006
Barcelona-El Prat	Barcelona	Spain	44154493	133755	307944	1209	BCN	LEBL	3	4	1918
Boston Logan	Boston	USA	36228822	274639	345722	1557	BOS	KBOS	5	6	1923
Charlotte Douglas	Charlotte	USA	46028962	1174470	541212	4473	CLT	KCLT	5	228	1936
Chengdu-Shuangliu	Chengdu	China	44039837	611991	319362	4700	CTU	ZUUU	2	495	1938
Chicago O'Hare	Chicago	USA	77960868	1566129	867635	2833	ORD	KORD	8	204	1901
Chongqing Jiangbei	Chongqing	China	32402196	313702	254360	4850	CKG	ZUCK	3	416	1990
Dallas – Fort Worth	Dallas – Fort Worth	USA	65670697	752874	672748	7318	DFW	KDFW	7	185	1974
Denver	Denver	USA	58264515	1478644	573528	13740	DEN	KDEN	6	1655	1995
Detroit Metropolitan Wayne County	Detroit	USA	34481254	205595	393427	2711	DTW	KDTW	6	196	1929
Dubai	Dubai	Dubai	83604000	2534706	453866	1400	DXB	OMDB	2	19	1960
Frankfurt am Main	Frankfurt am Main	Germany	60792388	2150000	462885	2160	FRA	EDDF	4	111	1936
Guangzhou Baiyun	Guangzhou	China	59732147	1692235	438231	1466	CAN	ZGGG	2	15	2004
Hongkong Chek Lap Kok	Hongkong	USA	70502000	4521000	411538	1255	HKG	VHHH	2	9	1998
Houston George Bush	Houston	USA	41615609	429795	479708	4027	IAH	KIAH	5	98	1969
Istanbul Ataturk	Istanbul	Turkey	67981446	2418934	464475	1462	ISL	LTBA	3	163	1912
Istanbul New	Istanbul	Turkey				7660	IST	LTFM	3	325	2018
Jakarta Soekarno-Hatta	Jakarta	Indonesia	56700000	414473	369748	1000	CGK	WIII	2	34	1994
Kuala Lumpur	Kuala Lumpur	Malaysia	52643011	643568	356414	1000	KUL	WMKK	2	21	1998
Kunming Changshui	Kunming	China	41998339	3994123	300446	1258	KMG	ZPPP	2	2103	1012
Las Vegas McCarran	Las Vegas	USA	47435640	101168	561428	1133	LAS	KLAS	4	665	1948
London Gatwick	London	UK	43119628	79588	280666	600	LGW	EGKK	2	60	1958
London Heathrow	London	UK	71671863	1541029	474963	1333	LHR	EGLL	2	25	1946
Los Angeles	Los Angeles	USA	88921827	2305335	697138	1386	LAX	KLAX	4	38	1928
Madrid-Barajas Adolfo Suárez	Madrid	Spain	50420583	415773	370158	3050	MAD	LEMD	4	610	1931
Manila NInoy Aquino	Manila	Philipines	39514782	648135	242615	0	MNL	RPLL	2	23	1948
Melbourne	Melbourne	Australia	35200000	275000	230000	968	MEL	YMML	2	132	1970
Mexico	Mexico	Mexico	32514264	408433	344100	7800	MEX	MMMX	2	2230	1952
Miami	Miami	USA	44584447	1548532	414157	1297	MIA	KMIA	3	8	1928
Minneapolis-Saint Paul	Minneapolis	USA	37505813	208742	413279	1376	MSP	KMSP	4	256	1923
Moskau Domodedowo	Moskau	Russia	30584615	135182	253864	1298	DME	UUDD	2	181	1964
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München Franz Josef Strauß	München	Germany	42261309	3953698	394428	1610	MUC	EDDM	2	448	1992
Mumbai Chhatrapati Shivaji	Mumbai	India	41154345	703209	385466	1307	BOM	VABB	2	11	1942
Neu-Delhi Indira Gandhi	Neu-Delhi	India	57793896	857439	397799	0	DEL	VIDP	3	237	1948
New York John F. Kennedy	New York	USA	58056288	1278707	440983	1995	JFK	KJFK	4	4	1942
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Paris Charles de Gaulle	Paris	France	65933145	2090000	472958	3500	CDG	LFPG	4	119	1974
Paris-Orly	Paris	France	32497846	151147	294464	1542	ORY	LFPO	3	89	1961
Philadelphia Guoji Jichang	Peking	China	51373480	1611147	434464	1440	PEK	ZBAA	3	116	1958
Philadelphia	Philadelphia	USA	36150490	1053810	394833	951	PHL	KPHL	3	11	1940
Phoenix Sky Harbor	Phoenix	USA	43383528	282182	448643	1214	PHX	KPHX	3	335	1979
Roma-Fiumicino Leonardo da Vinci	Rome	Italia	41744769	168903	314167	1660	FCO	LIRF	4	5	1961
San Francisco	San Francisco	USA	53186585	483223	498368	2093	SFO	KSFO	4	4	1927
São Paulo Guarulhos	São Paulo	Brasilia	36696326	205384	267746	1377	GRU	SBGR	2	750	1985

Store to database for further processing

Semantic Search Pattern – Customer Use Cases

I need a curved monitor at least 27” under 100€ with 2 USB ports

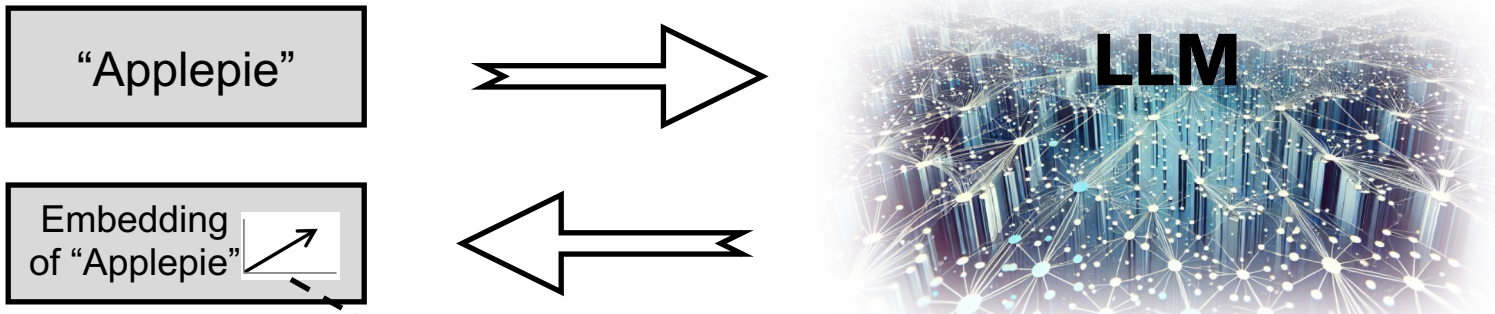
A natural orange flavor not based on alcohol

I need a replacement for a 3 phase engine with 30KW minimum

Common Pattern:

- User / customer needs to find an item / product in a large and complex database.
- Generative AI / LLMs can help to use natural language for the search, bridging semantic differences in query vs. data

GenAI Basics – Similarity Search



airportname	city	country	pax2016	freight2016	moves2016	areaha	code	codeicao	slb	height	openingyear
Amsterdam Schiphol	Amsterdam	Netherlands	63625664	1662282	496256	2787	AMS	EHAM	6	-4	
Hartsfield-Jackson Atlanta	Atlanta	USA	104258124	648595	898356	1518	ATL	KATL	5	316	
Bangkok-Suvarnabhumi	Bangkok	Thailand	55892428	1351878	336345	3100	BKK	VTBS	2	2	
Barcelona-El Prat	Barcelona	Spain	44154693	132755	307864	1300	BCN	LEBL	3	4	
Boston Logan	Boston	USA	36288042	279836	391222	971	BOS	KBOS	5	6	
Charlotte Douglas	Charlotte	USA	44422022	154477	545742	2428	CLT	KCLT	4	228	
Chengdu-Shuangliu	Chengdu	China	46039037	611591	319382	698	CTU	ZUUU	2	495	
Chicago O'Hare	Chicago	USA	77960508	1566129	867635	2833	ORD	KORD	8	204	
Chongqing Jiangbei	Chongqing	China	32402196	318782	254360	485	CKG	ZUCK	3	416	
Dallas - Fort Worth	Dallas - Fort Worth	USA	65670697	752074	672748	7318	DFW	KDFW	7	185	
Denver	Denver	USA	58266515	247564	572520	13760	DEN	KDEN	6	1655	
Detroit Metropolitan Wayne County	Detroit	USA	34401254	205595	393427	2711	DTW	KDTW	6	196	
Dubai	Dubai	Dubai	83654000	2534786	453886	1400	DXB	OMDB	2	19	
Frankfurt am Main	Frankfurt am Main	Germany	60792308	2150000	462885	2160	FRA	EDDF	4	111	
Guangzhou Baiyun	Guangzhou	China	59732147	1652215	435231	1456	CAN	ZGGG	2	15	
Hongkong Chek Lap Kok	Hongkong	USA	70502000	4521000	411530	1255	HKG	VHHH	2	9	
Houston George Bush	Houston	USA	41615689	429785	470780	4452	IAH	KIAH	5	30	
Istanbul Atatürk	Istanbul	Turkey	67981446	2410934	464625	947	ISL	LTBH	3	50	
Istanbul New	Istanbul	Turkey	0	0	0	7660	IST	LTFM	4	60	
Jakarta Soekarno-Hatta	Jakarta	Indonesia	58700000	42473	369740	1800	CGK	WIII	2	10	
Kuala Lumpur	Kuala Lumpur	Malaysia	52643511	642558	356614	1000	KUL	WMKK	2	21	
Kunming Changshui	Kunming	China	41980339	355423	300486	1250	KMG	ZPPP	2	2103	
Las Vegas McCarran	Las Vegas	USA	47435648	101168	541428	1133	LAS	KLAS	4	665	
London Gatwick	London	UK	43119628	79588	280666	680	LGW	EGKK	2	60	
London Heathrow	London	UK	75671863	1541029	474963	1333	LHR	EGLL	2	25	
Los Angeles	Los Angeles	USA	80921527	2205335	697138	1386	LAX	KLAX	4	38	
Madrid-Barajas Adolfo Suárez	Madrid	Spain	50420583	415773	378150	3050	MAD	LEMD	4	610	
Manila Ninoy Aquino	Manila	Philipines	39516782	460135	242615	0	MNL	RPLL	2	23	
Melbourne	Melbourne	Australia	35200000	275000	238000	960	MEL	YMML	2	132	
Mexiko	Mexico	Mexico	41710254	483433	448147	746	MEX	MMMX	2	2230	
Miami	Miami	USA	44584603	2228733	414234	1307	MIA	KMIA	4	2	
Minneapolis-Saint Paul	Minneapolis	USA	37505521	206942	413279	1376	MSP	KMSP	4	256	
Moskau Domodedowo	Moskau	Russia	30504515	133182	253084	1280	DME	UUDD	2	181	
Moskau Scheremetjewo	Moskau	Russia	34030000	196984	272970	0	SVO	UUEE	2	196	
München Franz Josef Strauß	München	Germany	42261309	353650	394430	1618	MUC	EDDM	2	448	
Mumbai Chhatrapati Shivaji	Mumbai	India	45154345	782289	305465	1307	BOM	VABB	2	11	
Neu-Delhi Indira Gandhi	Neu-Delhi	India	57703896	857419	397799	0	DEL	VIDP	3	237	
New York John F. Kennedy	New York	USA	58956288	1278707	448903	1995	JFK	KJFK	4	4	
New York LaGuardia	New York	USA	29786769	7500	369987	275	LGA	KLGA	2	4	
New York Newark Liberty	New York	USA	40351331	719006	431595	820	EWR	KEWR	3	6	
Orlando	Orlando	USA	41923399	189649	316981	5381	MCO	KMCO	4	29	
Paris Charles de Gaulle	Paris	France	65933145	2090000	472950	3500	CDG	LFPG	4	119	
Paris-Orly	Paris	France	31237865	115440	234453	1540	ORY	LFPO	3	89	
Peking Shoudu Guoji Jichang	Peking	China	94393000	1831167	606086	961	PEK	ZBAA	3	35	
Philadelphia	Philadelphia	USA	30155090	445810	394022	971	PHL	KPHL	4	11	
Phoenix Sky Harbor	Phoenix	USA	43383528	282152	440643	1214	PHX	KPHX	3	335	
Roma-Fiumicino Leonardo da Vinci	Roma	Italia	41744769	160903	314167	1660	FCO	LIRF	4	5	
San Francisco	San Francisco	USA	53106505	483223	450388	2093	SFO	KSFO	4	4	
São Paulo Guarulhos	São Paulo	Brasilia	36596326	205304	267746	1377	GRU	SBGR	2	750	

```
SELECT ... FROM my_own_table
   WHERE ...
   ORDER BY vector_similarity
```

95% Applepie
90% Apfelkuchen
60% Pear Crumble
...

GenAI Basics – Text2SQL

The user is asking:

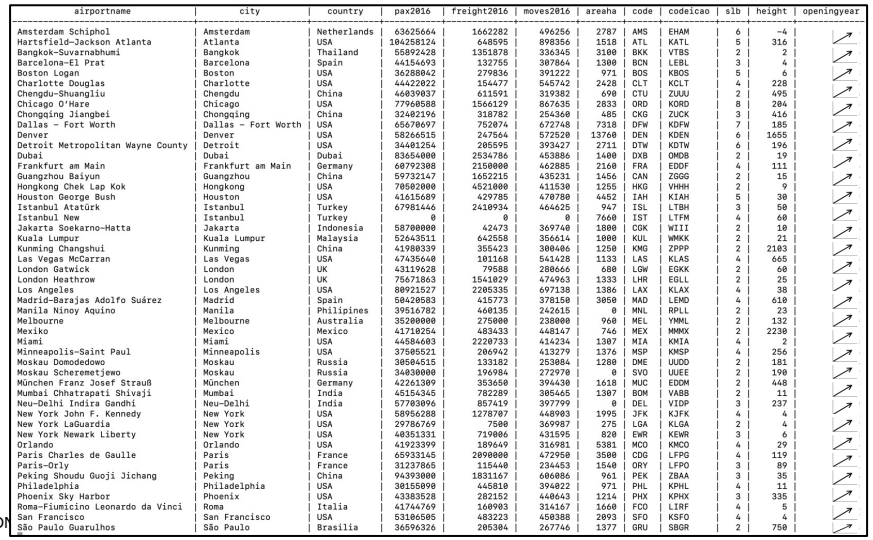
“I need a flavor without alcohol”

My table is the following:

CREATE TABLE myProducts (
id CHAR(10) COMMENT ‘identifier’,
type CHAR(20) COMMENT ‘type of product, flavor … ’,
…
alc BOOLEAN COMMENT ‘does it contain alcohol?’)

Return an SQL statement …





airportname	city	country	pax2016	freight2016	moves2016	areaha	code	codeicao	slb	height	openingyear
Amsterdam Schiphol	Amsterdam	Netherlands	63625664	1662282	496256	2787	AMS	EHAM	6	-4	
Hartsfield-Jackson Atlanta	Atlanta	USA	104258124	648595	898356	1518	ATL	KATL	5	316	
Bangkok-Suvarnabhumi	Bangkok	Thailand	55892428	1351878	336345	3100	BKK	VTBS	2	2	
Barcelona-El Prat	Barcelona	Spain	44154693	132755	307864	1300	BCN	LEBL	3	4	
Boston Logan	Boston	USA	36288042	279836	391222	971	BOS	KBOS	5	6	
Charlotte Douglas	Charlotte	USA	44422022	154477	545742	2428	CLT	KCLT	4	228	
Chengdu-Shuangliu	Chengdu	China	46039037	611591	319382	690	CTU	ZUUU	2	495	
Chicago O'Hare	Chicago	USA	77960588	1566129	867635	2833	ORD	KORD	8	204	
Chongqing Jiangbei	Chongqing	China	32402196	318782	254360	485	CKG	ZUCK	3	416	
Dallas – Fort Worth	Dallas – Fort Worth	USA	65670697	752074	672748	7318	DFW	KDFW	7	185	
Denver	Denver	USA	58266515	247564	572520	13760	DEN	KDEN	6	1655	
Detroit Metropolitan Wayne County	Detroit	USA	34401254	205595	393427	2711	DTW	KDTW	6	196	
Dubai	Dubai	83654000	2534786	453886	1400	DXB	OMDB	2	19		
Frankfurt am Main	Frankfurt am Main	Germany	60792308	2150000	462885	2160	FRA	EDDF	4	111	
Guangzhou Baiyun	Guangzhou	China	59732147	1652215	435231	1456	CAN	ZGGG	2	15	
Hongkong Chek Lap Kok	Hongkong	USA	70502000	4521000	411530	1255	HKG	VHHH	2	9	
Houston George Bush	Houston	USA	41615689	429785	470780	4452	IAH	KIAH	5	30	
Istanbul Atatürk	Istanbul	Turkey	67981446	2410934	464625	947	ISL	LTBH	3	50	
Istanbul New	Istanbul	Turkey	0	0	0	7660	IST	LTFM	4	60	
Jakarta Soekarno-Hatta	Jakarta	Indonesia	58700000	42473	369740	1800	CGK	WIII	2	10	
Kuala Lumpur	Kuala Lumpur	Malaysia	52643511	642558	356614	1000	KUL	WMKK	2	21	
Kunming Changshui	Kunming	China	41980339	355423	300406	1250	KMG	ZPPP	2	2103	
Las Vegas McCarran	Las Vegas	USA	47435640	101168	541428	1133	LAS	KLAS	4	665	
London Gatwick	London	UK	43119628	79588	280666	680	LGW	EGKK	2	60	
London Heathrow	London	UK	75671863	1541029	474963	1333	LHR	EGLL	2	25	
Los Angeles	Los Angeles	USA	80921527	2205335	697138	1386	LAX	KLAX	4	38	
Madrid-Barajas Adolfo Suárez	Madrid	Spain	50420583	415773	378150	3050	MAD	LEMD	4	610	
Manila Ninoy Aquino	Manila	Philipines	39516782	440135	242615	0	MNL	RPLL	2	23	
Melbourne	Melbourne	Australia	35200000	275000	238000	960	MEL	YMML	2	132	
Mexiko	Mexico	Mexico	41710254	483433	448147	746	MEX	MMMX	2	2230	
Miami	Miami	USA	44584603	2220733	414234	1307	MIA	KMIA	4	2	
Minneapolis-Saint Paul	Minneapolis	USA	37505521	206942	413279	1376	MSP	KMSP	4	256	
Moskau Domodedowo	Moskau	Russia	30504515	133182	253084	1280	DME	UUDD	2	181	
Moskau Scheremetjewo	Moskau	Russia	34030000	196984	272970	0	SVO	UUEE	2	190	
München Franz Josef Strauß	München	Germany	42261309	353650	394430	1618	MUC	EDDM	2	448	
Mumbai Chhatrapati Shivaji	Mumbai	India	45154345	782289	385465	1307	BOM	VABB	2	11	
Neu-Delhi Indira Gandhi	Neu-Delhi	India	57703096	857419	397799	0	DEL	VIDP	3	237	
New York John F. Kennedy	New York	USA	58956288	1278707	448903	1995	JFK	KJFK	4	4	
New York LaGuardia	New York	USA	29786769	7500	369987	275	LGA	KLGA	2	4	
New York Newark Liberty	New York	USA	40351331	719006	431595	820	EWR	KEWR	3	6	
Orlando	Orlando	USA	41923399	189649	316981	5381	MCO	KMCO	4	29	
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Paris-Orly	Paris	France	31237865	115440	234453	1540	ORY	LFPO	3	89	
Peking Shoudu Guoji Jichang	Peking	China	94393000	1831167	600086	961	PEK	ZBAA	3	35	
Philadelphia	Philadelphia	USA	30155090	445810	394022	971	PHL	KPHL	4	11	
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Roma-Fiumicino Leonardo da Vinci	Roma	Italia	41744769	160903	314167	1660	FCO	LIRF	4	5	
San Francisco	San Francisco	USA	53106505	483223	450388	2093	SFO	KSFO	4	4	
São Paulo Guarulhos	São Paulo	Brasilia	36596326	205304	267746	1377	GRU	SBGR	2	750	

SELECT … FROM myProducts
WHERE type = ‘**flavor**’
AND **alcohol** = **false**

Product	Type	Alcohol
11	Flavor	False
20044	Flavor	False
402	Flavor	False

Generative AI – Anti-Patterns and Pitfalls

Full semantics not contained in the data or text

- Only codes, no speaking names: material number, but no description
- Encodings in numbers:
  1234567890 => hierarchy level 1
  12**345**67890 => hierarchy level 2
  12345**67890** => hierarchy level 3
- Company / group specific terminology: “high five” as the top five KPIs

Knowledge / semantics not available for the LLM

- Not explicitly stated in documents or data
- Context like systems and landscape not known to AI, but user expects it “AI should know…”
- Knowledge / facts can change over time

Question Answering Pattern – Customer Use Cases



How many vacation days am I eligible for and how many do I have left actually?

I am facing the following error situation, help me out

How did the offers from supplier X evolve over the time?

I receive a list of payments as PDF which I need to match with data in my system.

How does the actual wheather impact the quality of the food products I need to buy?

Common Pattern:

- User is asking questions which can be answered based on documents and / or lookup in a system
- Generative AI helps to find the relevant sections in documents or access the relevant API in the system and to generate the response

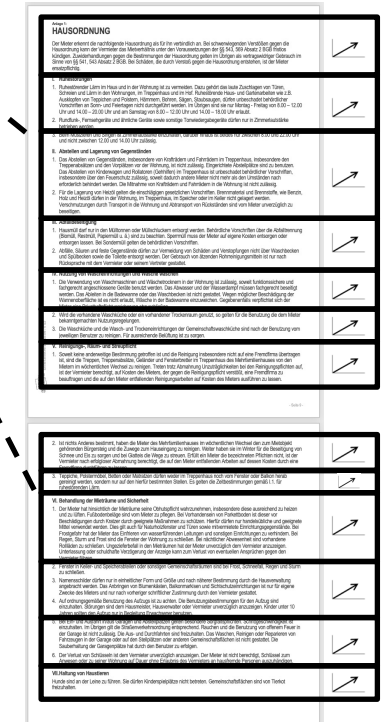
GenAI Basics – Document RAG (Retrieval Augmented Generation)

The user asked:

“What am I allowed …”

Answer using the following snippets exclusively::





LLM

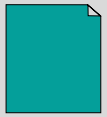
My docs
cut in pieces
with vectors

Selected by
similarity search
(see other slide)

You are allowed to do Kehrwoche once a week.

GenAI Basics – Document Analysis / Preprocessing

Here is a document:



Analyze and extract the following:
- **title**: title of the document
- **author**: author of the document
- **type**: which type: docu, fiction, dict
- **hero**: main actor
- **plot**: summary in 10 words max

Return a nice JSON structure ...

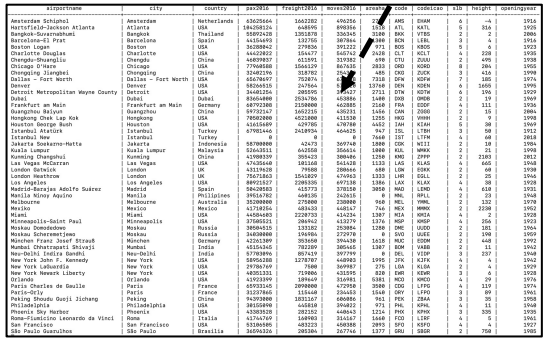



```
{
  "title":  "HH's Guide",
  "author": "Douglas A.",
  "type":   "fiction",
  "hero":   "Arthur Dent",
  "plot":   "Arthur
explores our galaxy and
the rest of the universe"
}
```

Store to database

Analyze or include in RAG





LLMs and Documents – Anti-Patterns and Pitfalls

Problems with document collections

- Statement on home office depends on country, federal country, industry, company, subsidiary, role (accountant vs. fork lifter driver)
  … and not always the more specific wins ➔ Principle of favorability (Günstigerprinzip)
- Outdated documents in collection
- Issues processing very large documents - document context vs. trained “knowledge”
  https://www.youtube.com/watch?v=D0BlztFXuTw

Problem with RAG

- Information is contained in pictures only, not in the text
- Changes listed within the document
- Question which are broad (including larger parts of document)



Agentic!
Use Cases & Patterns

Agents – Customer Use Cases

I need support in bookings:
- check the defined rules
- lookup the relevant documents
- infer from actual bookings

Pre-Clarify Incidents:
- match against existing tickets
- categorize incident
- suggest measures based on knowledge base

Handle user request including:
- Simple question on documents or system lookup
- Booking of a hotel or flight as required
- Cancel a booking
- Request a change of the booking

Common Pattern:

- The task requires a number of steps and the application of different tools in order to find a solution or answer
- The exact approach, number and order of tools to be used is not clear upfront. It needs to be determined through reasoning, maybe even a question back to the user.
- Typical tools: API call, web search, document lookup...

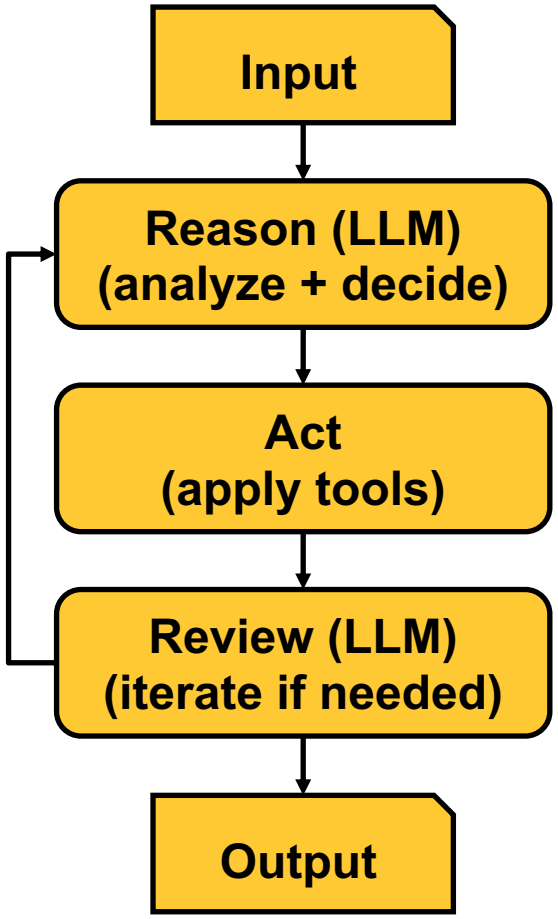
AI Agents – Pragmatic View

AI Agent = Purpose + Tools

Purpose of TradeFair agent: You are an assistant on trade fairs, you will answer questions about trafe fairs and book hotels and travels to trade fairs ... (more details follow)

Tools of TradeFair agent:

- Web search – check dedicated web sites for trade fairs
- Extract Information – determine purpose, dates and locations of a trade fair
- API calls – search and book hotels, flights, trains ...
- DB lookup – search for trade events criteria in a local database table
- Calculator – compare distances, calculate dates
- Human Input – ask user before booking a hotel



GenAI Basics – AI Agent in Action

For the trade fair
in October 2026 in Paris,
get me a ticket,
book a hotel
(first day-1, end day+1)
and travel (train or flight)





Here are your results:

1. Ticket for SIAL Paris
   Oct 17th – 21st 2026
2. Booking:
   Paris Hilton, 16th – 22nd
3. Flight ticket:
   FRA to CDG, 16th – 22nd

Web Tool | Ticket API | Hotel API | Flight API

Agents – Anti-Patterns and Pitfalls



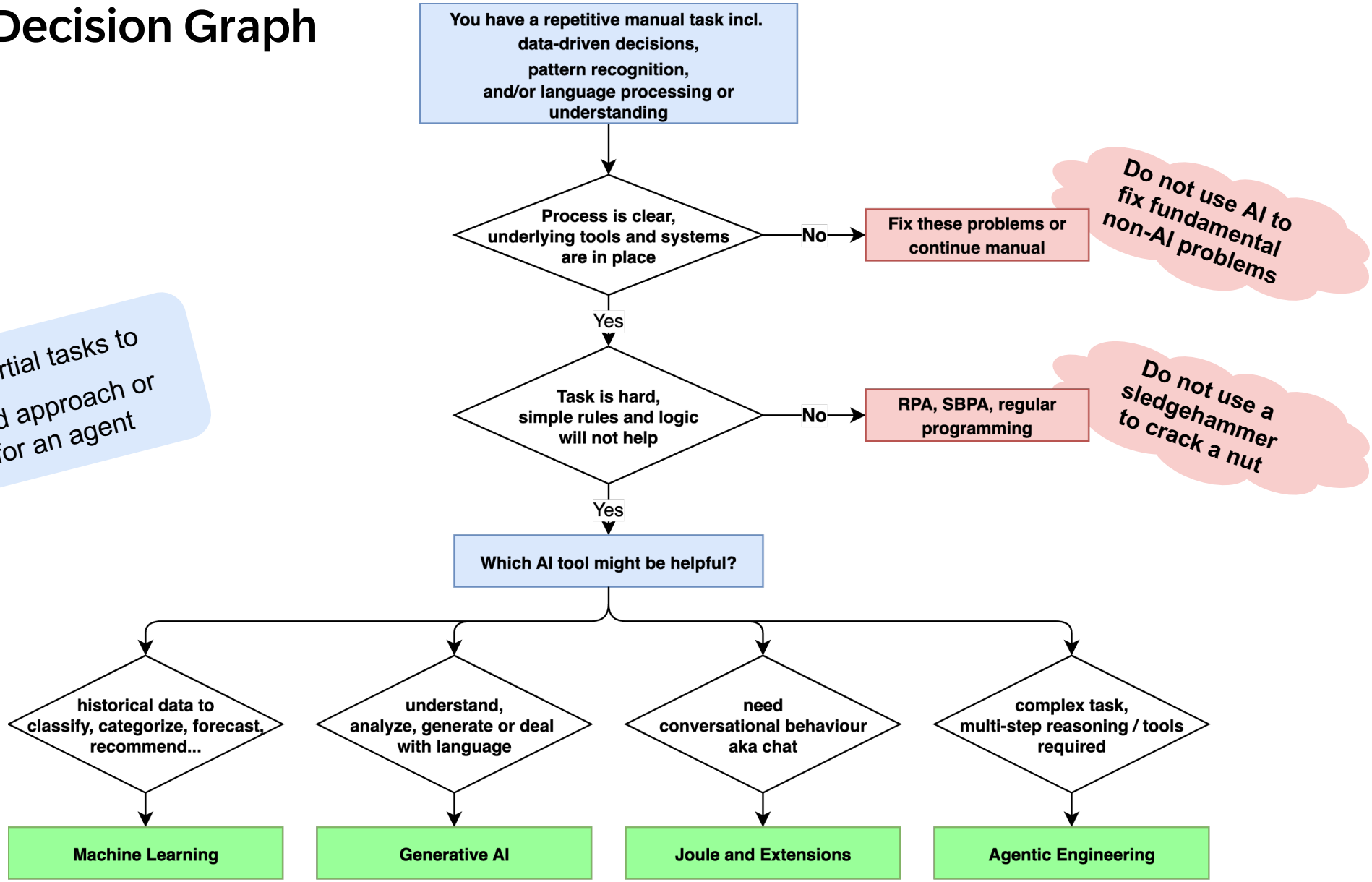
If the process is clear, set of tools fixed, order of actions straight – why do you need an agent?

Also agents can halucinate, they use LLMs – the halucination can happen on level of instructions and tool usage
➔ need for harness, evals – proper agent infrastructure



“AI or not AI”

Simplified Decision Graph



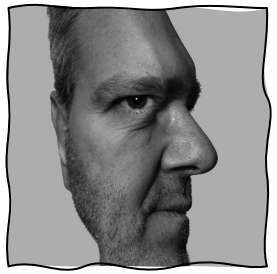
Apply also to partial tasks to
a. build a hybrid approach or
b. build a tool for an agent

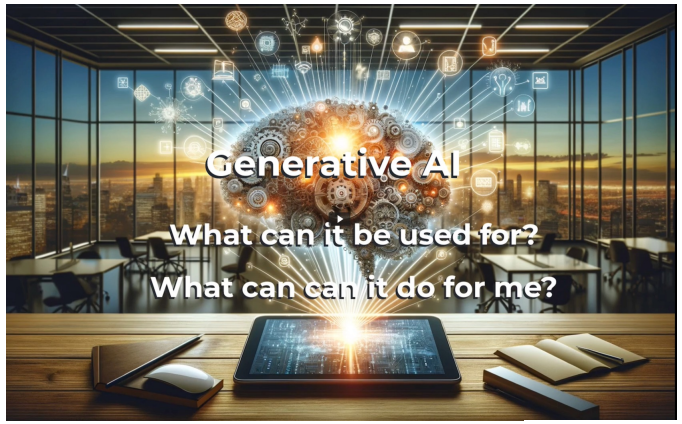
More detailed version: https://architecture.learning.sap.com/docs/ai-golden-path

Thank You

Contact information:

Adi Pleyer
adi.pleyer@sap.com





Generative AI in 5 minutes:
https://url.sap/qdpse3

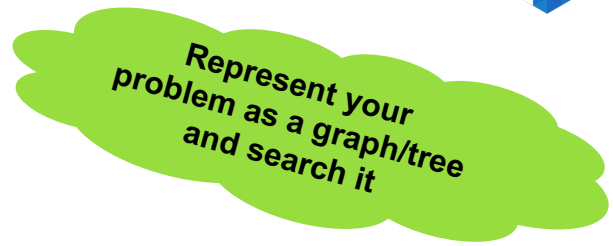
OFFICE OF THE CTO

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Backup

Searching Ways – Shortest Path Problem



Shortest path problem in graph theory: find a path between two nodes such that the sum of the weights of edges is minimized

Applications:

- **GPS and Map Navigation** - Finding the fastest or shortest driving/walking route between two locations
- **Internet Routing** - Routers compute the shortest path for sending packets across networks
- **Video Game Pathfinding** - NPCs and enemies move intelligently through game worlds with obstacles
- **Robot Motion Planning** - determine collision-free, minimum-cost paths in real environments
- **Social Network Analysis** - Find “degrees of separation” or the shortest connection between two people

https://en.wikipedia.org/wiki/Shortest_path_problem
Dijkstra Algorithm: https://en.wikipedia.org/wiki/Dijkstra%27s_algorithm

Classical Optimization Methods

Optimization methods

- **Hill Climbing** – a simple local search method
- **Simulated Annealing** – a probabilistic optimization technique that allows occasional “downhill” moves
- **Genetic Algorithms** (Evolutionary Optimization) – population-based search inspired by natural selection
- **A* Search** (Optimal Path/State Search) – actual cost + heuristic estimate to find globally optimal solutions
- **Linear Programming** (LP) – framework for planning, resource allocation, constraint satisfaction, decision-making

Applications of AI optimization methods

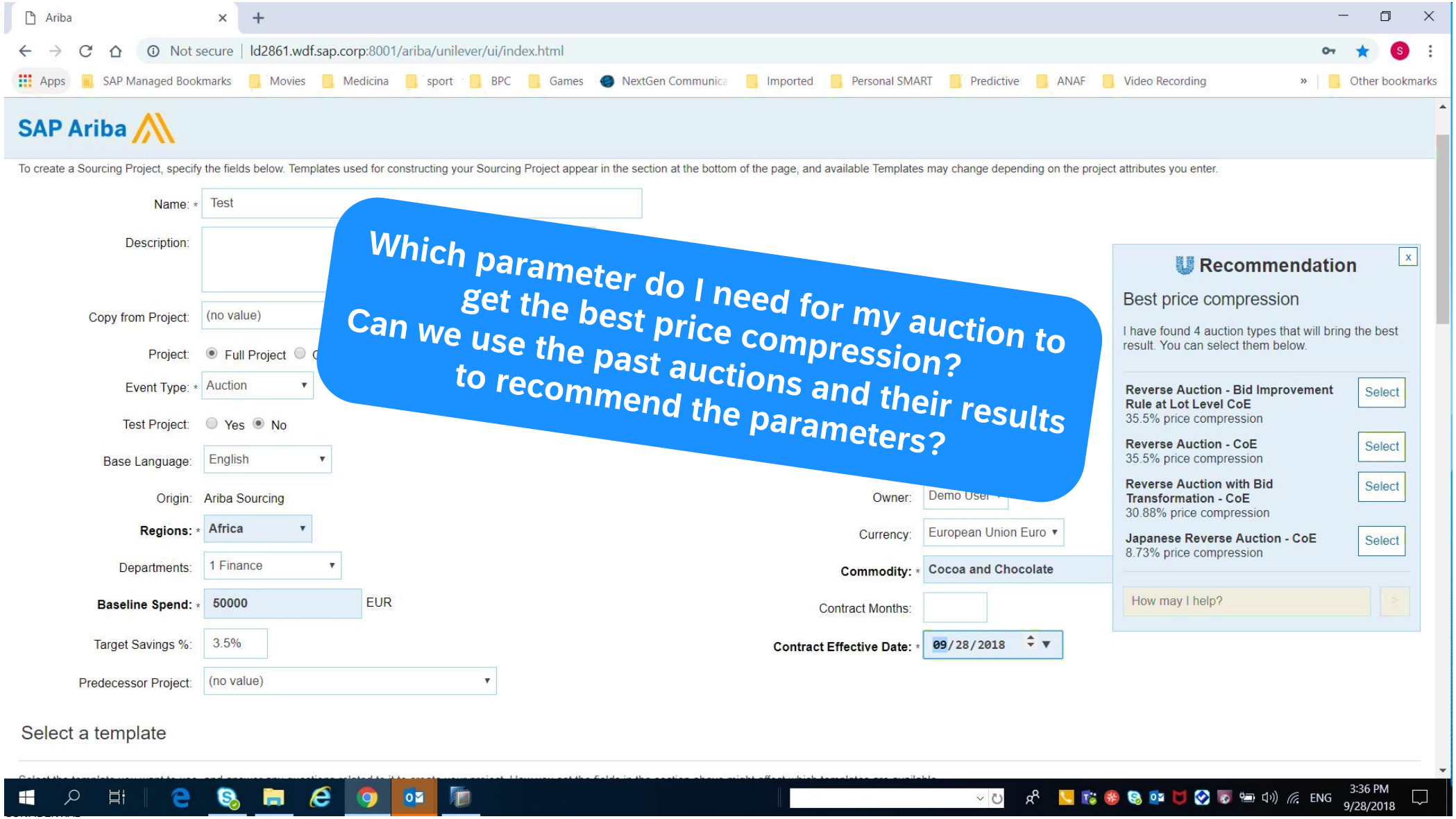
- **Scheduling and Timetabling** – tasks, resource allocation, job scheduling, school timetables.
- **Route Planning and Navigation** – Optimal paths for robots, vehicles, delivery systems, and logistics
- **Resource Allocation** – Optimizing budgets, supply chains, manufacturing processes, and workload distribution.

Market Share Forecasting – Ottogi



How will our market share look like
in the next 3 months?
Can we extrapolate the historical time series?

Auction Parameter Recommendation – Unilever



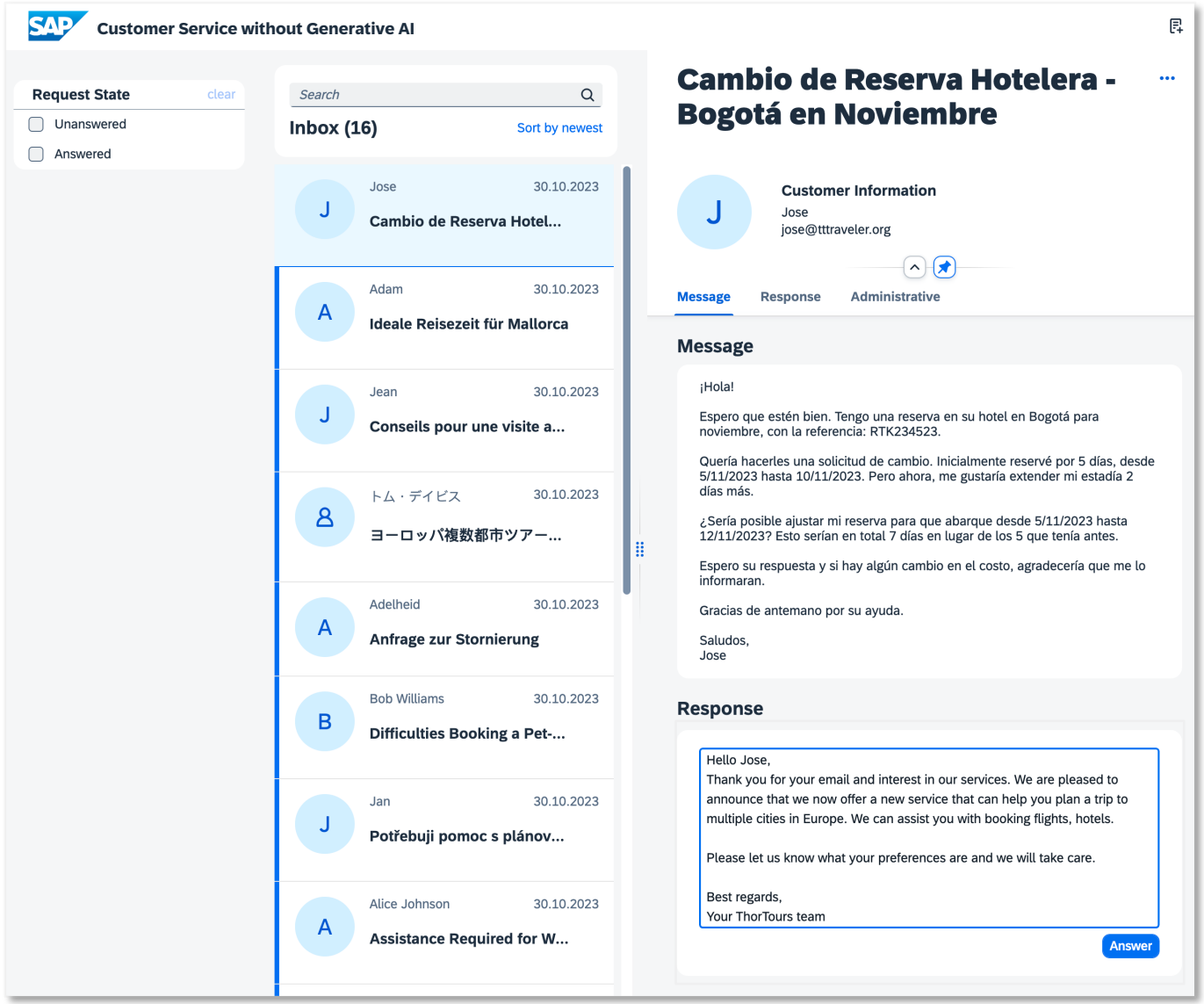
GenAI Mail Insights – The Business Context

Reference Application

What is our situation?

- Customer Support
- One person (or team) is in charge to respond to a **mass of requests**
- Professionally, only **one language** is spoken
- Inquiries are centered around a **few recurring topics**

This is not a complete real world scenario but many similar situations exist and can be adapted



Customer Service without Generative AI features

Reducing Accounts Payable Workload with Custom AI

Customer Project

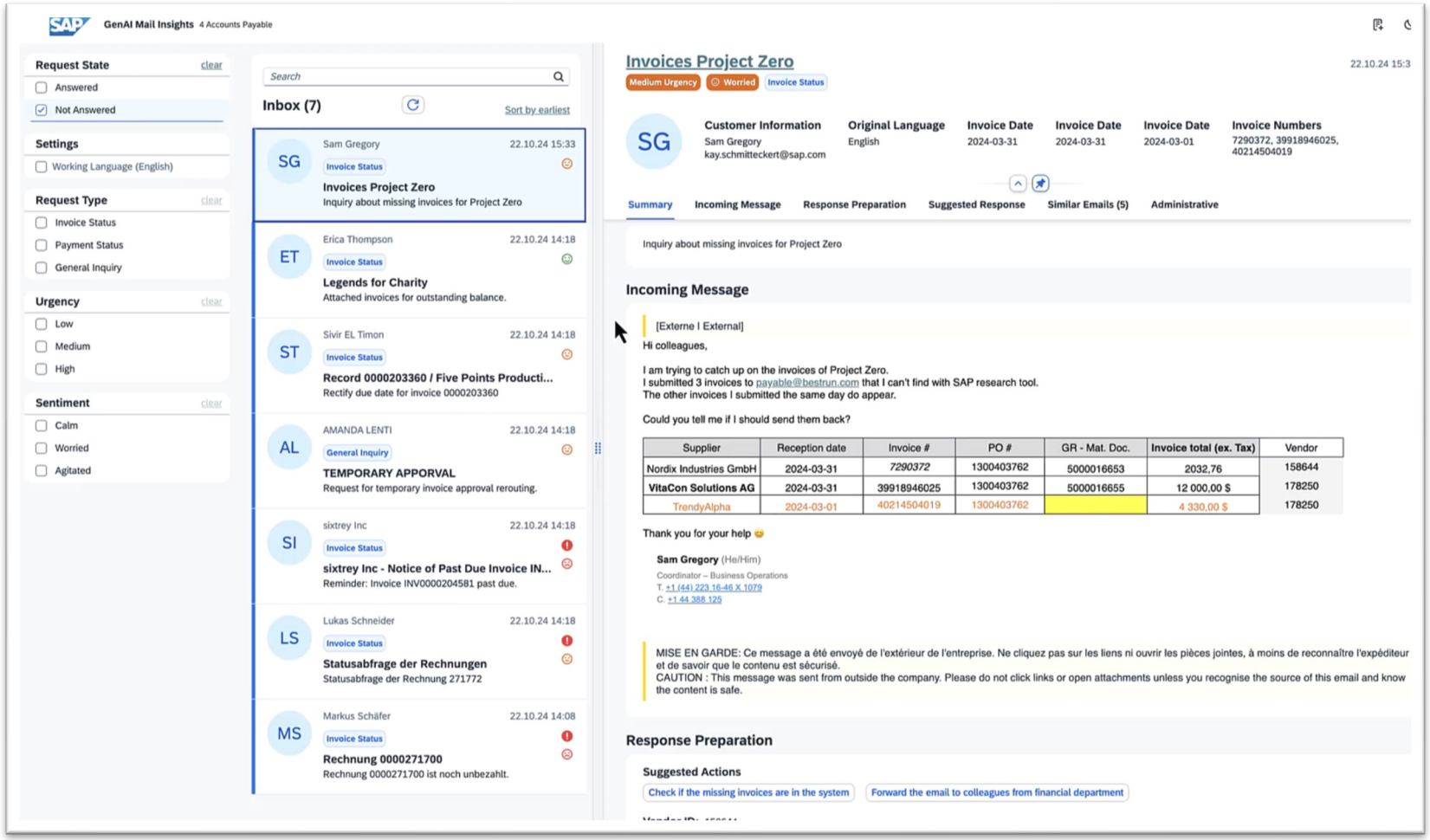
The customer receives thousands of invoice-related emails each month, creating a heavy manual workload for the Accounts Payable team. To streamline this, they implemented Generative AI to analyze invoice statuses, identify payment delays, and automate responses – reducing effort and improving vendor and customer satisfaction.

Custom AI based on AI Foundation

- Generative AI Hub with Orchestration Service
- SAP Document AI for Invoice Processing
- SAP HANA Cloud's Vector Engine to find similar cases

Resources

Based on *GenAI Mail Insights*
SAP Cloud SDK for AI
Reference Architecture: Generative AI on SAP BTP



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Request State clear
- [ ] Answered
- [x] Not Answered

Settings
- [ ] Working Language (English)

Request Type clear
- [ ] Invoice Status
- [ ] Payment Status
- [ ] General Inquiry

Urgency clear
- [ ] Low
- [ ] Medium
- [ ] High

Sentiment clear
- [ ] Calm
- [ ] Worried
- [ ] Agitated

Search

Inbox (7) Sort by earliest

SG — Sam Gregory — 22.10.24 15:33 — Invoice Status
Invoices Project Zero
Inquiry about missing invoices for Project Zero

ET — Erica Thompson — 22.10.24 14:18 — Invoice Status
Legends for Charity
Attached invoices for outstanding balance.

ST — Sivir EL Timon — 22.10.24 14:18 — Invoice Status
Record 0000203360 / Five Points Producti...
Rectify due date for invoice 0000203360

AL — AMANDA LENTI — 22.10.24 14:18 — General Inquiry
TEMPORARY APPORVAL
Request for temporary invoice approval rerouting.

SI — sixtrey Inc — 22.10.24 14:18 — Invoice Status
sixtrey Inc - Notice of Past Due Invoice IN...
Reminder: Invoice INV0000204581 past due.

LS — Lukas Schneider — 22.10.24 14:18 — Invoice Status
Statusabfrage der Rechnungen
Statusabfrage der Rechnung 271772

MS — Markus Schäfer — 22.10.24 14:08 — Invoice Status
Rechnung 0000271700
Rechnung 0000271700 ist noch unbezahlt.

Invoices Project Zero

22.10.24 15:33

Medium Urgency | Worried | Invoice Status

SG

Customer Information	Original Language	Invoice Date	Invoice Date	Invoice Date	Invoice Numbers
Sam Gregory kay.schmitteckert@sap.com	English	2024-03-31	2024-03-31	2024-03-01	7290372, 39918946025, 40214504019

Summary | Incoming Message | Response Preparation | Suggested Response | Similar Emails (5) | Administrative

Inquiry about missing invoices for Project Zero

Incoming Message

[Externe | External]

Hi colleagues,

I am trying to catch up on the invoices of Project Zero.
I submitted 3 invoices to payable@bestrun.com that I can't find with SAP research tool.
The other invoices I submitted the same day do appear.

Could you tell me if I should send them back?

Supplier	Reception date	Invoice #	PO #	GR - Mat. Doc.	Invoice total (ex. Tax)	Vendor
Nordix Industries GmbH	2024-03-31	*7290372*	1300403762	5000016653	2032,76	158644
VitaCon Solutions AG	2024-03-31	39918946025	1300403762	5000016655	12 000,00 $	178250
TrendyAlpha	2024-03-01	40214504019	1300403762		4 330,00 $	178250

Thank you for your help

Sam Gregory (He/Him)
Coordinator – Business Operations
T. +1 (44) 223 16-46 X 1079
C. +1 44 388 125

MISE EN GARDE: Ce message a été envoyé de l'extérieur de l'entreprise. Ne cliquez pas sur les liens ni ouvrir les pièces jointes, à moins de reconnaître l'expéditeur et de savoir que le contenu est sécurisé.
CAUTION : This message was sent from outside the company. Please do not click links or open attachments unless you recognise the source of this email and know the content is safe.

Response Preparation

Suggested Actions

Check if the missing invoices are in the system | Forward the email to colleagues from financial department

Vendor ID: 158644

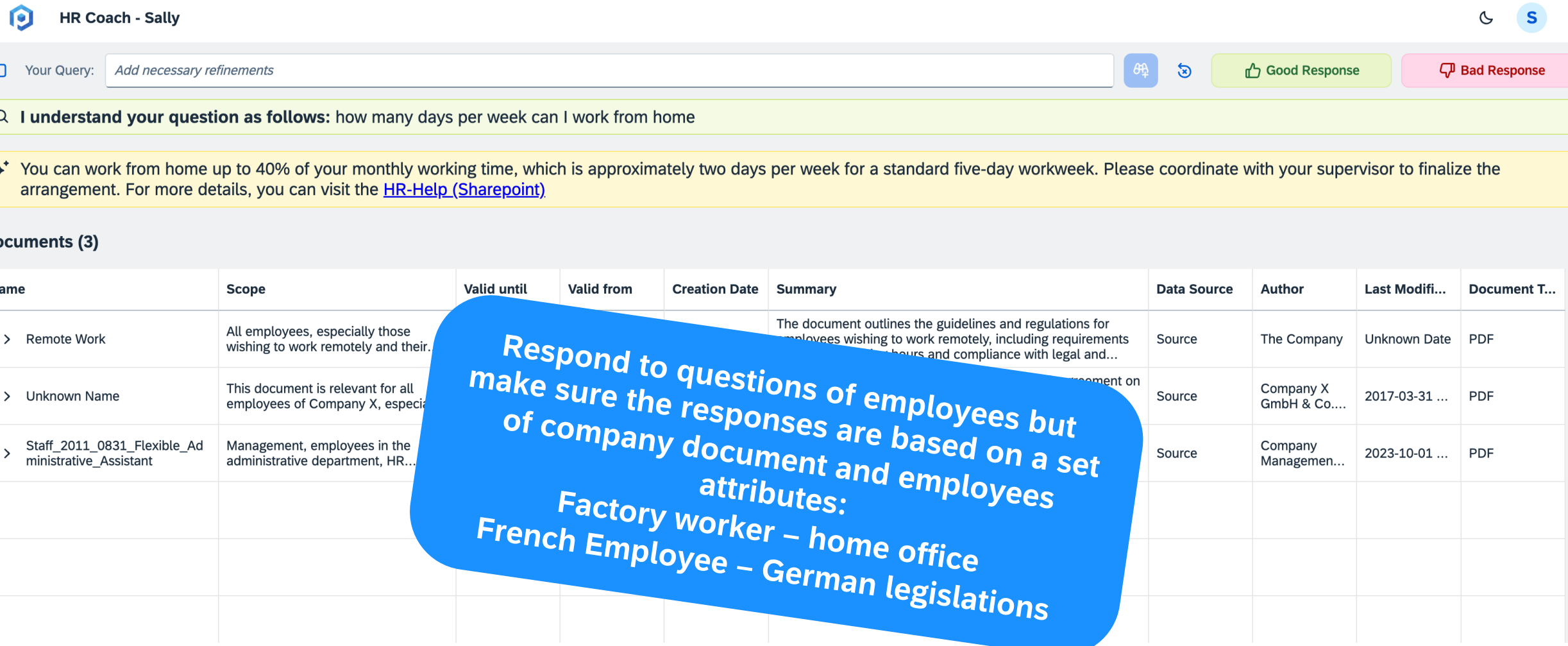
Customer Use Case – Find a Product in a Complex Database

Similarity	Product Code	Product Name	Product Type	Colour Sensory	Taste Aroma 1	Cloudiness Sensory	Consistency	Brix Uncorrected	Alcohol	Application Fit	Vitamins	Sweetener	L1 Category
91.27%	H03181	MOJITO 3181	Liquid Flavour	yellow	mojito	clear		40.0 - 80.0 ° Brix	No		No	No	NPI Natural Perfomance Ingr
91.23%	K14220	natural Orange Flav...	Liquid Flavour	colourless - sli...	orange	clear to slightly clo...	liquid	54.01 - 58.03 ° ...	No	Flavoured Ca...	No	No	NPI Natural Perfomance Ingr
91.19%	K80651	Halal natural Orang...	Liquid Flavour	colourless - sli...	orange	clear to slightly clo...	liquid	54.02 - 58.04 ° ...	No	Flavoured Ca...	No	No	NPI Natural Perfomance Ingr
91.18%	H01152	ORANGE OIL EXCE...	Liquid Flavour	yellow	orange	clear	liquid	65 - 85 ° Brix	No		No	No	NPI Natural Perfomance Ingr
91.12%	H01165	Flavour Sweet Ora...	Liquid Flavour	yellow	orange	clear	liquid	48 - 55 ° Brix	No		No	No	NPI Natural Perfomance Ingr
91.10%	K15072	nat			orange	clear to slightly clo...	liquid	54.1 - 58.12 ° Brix	No	Flavoured Ca...	No	No	NPI Natural Perfomance Ingr
91.07%	B58612	na					liquid	54.06 - 58.02 ° ...	No	Non-Alcoholi...	No	No	NPI Natural Perfomance Ingr
91.06%	K87001	C						.12 - 73.27 ° ...	No	Flavoured Mil...	No	No	NPI Natural Perfomance Ingr
91.05%	K14535	C						3.12 - 72.79 ° ...	No	Flavoured Ca...	No	No	NPI Natural Perfomance Ingr
91.05%	K83982	natural Mandarin Fl...	Liquid					5.88 - 49.33 ° ...	No	Flavoured Ca...	No	No	NPI Natural Perfomance Ingr
91.05%	K11863	Orange Flavouring	Liquid Flavour	yellow	orange			53.93 - 57.95 ° ...	No	Flavoured Ca...	No	No	NPI Natural Perfomance Ingr
91.04%	B25391	natural Lime Flavou...	Liquid Flavour	yellow	lime	clear to slightly clo...	liquid	54.73 - 58.74 ° ...	No	Beer-Mix Bev...	No	No	NPI Natural Perfomance Ingr
91.00%	B76571	natural Flavouring (...	Liquid Flavour	colourless - sli...	blood orange	clear to slightly clo...	liquid	57.05 - 60.16 ° ...	No	Energy Drinks...	No	No	NPI Natural Perfomance Ingr
90.98%	K87005	natural Orange Flav...	Liquid Flavour	brown	orange	clear to slightly clo...	liquid	71.80 - 75.75 ° ...	No	Juices, Nectars	No	No	NPI Natural Perfomance Ingr
90.98%	K84654	natural Orange Flav...	Liquid Flavour	orange	orange	clear to slightly clo...	liquid	70.64 - 72.68 ° ...	No	Flavoured Ca...	No	No	NPI Natural Perfomance Ingr
90.96%	H93605	Nat Orange Fl Wonf	Liquid Flavour	orange	orange		liquid	11.24 - 31.34 ° ...	No		No	No	NPI Natural Perfomance Ingr

Which attributes to use and which are the right values to search for?

...this is a real world situation

Customer Use Case – Answer Questions on a Defined Set of Documents



Respond to questions of employees but make sure the responses are based on a set of company document and employees attributes:

Factory worker – home office

French Employee – German legislations

AI Agents – Definition and Potential Use Case

AI Agents solve problems where the way to solution is not fixed

- receive input
- reason and make decisions
- take actions with provided tools
- interact with users, their environment, or other agents (A2A)

Example TradeFair Agent: give information about and book visits to Trade Fairs:

- Which trade fair is coming up next?
- Which trade fairs will be relevant in the rest of the year?
- For the trade fair in March, get me a ticket, book a hotel (first day - 1 until end day + 1) and travel (train or flight)
- If a new relevant fair appears, block the calendars of me and my team



Hybrid / Neuro-Symbolic AI – Use Cases

Route navigation
the world is a graph but the traffic situation needs statistics and forecasting

Improve search in products, combine recommendations and reasoning via Knowledge Graphs

Self-driving cars:
need object and lane recognition and still enforce traffic rules

Fraud detection in finance:
detect unusual transaction patterns and cover compliance with regulations

Common Pattern:

- Neural nets / ML / LLMs are flexible but opaque
- Symbolic AI can be rigid but explainable

➔ Combination of both can make solution more accurate and trustworthy