Revolutionising the insurance industry with gen AI

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Disclaimer

This presentation has been prepared for general purposes only and does not purport to be and is not a substitute for specific professional advice. While the matters identified are believed to be generally correct, before any specific action is taken, specific advice on the circumstances in question should be obtained.

Agenda

- 1. Introduction to generative AI
- 2. Risks and regulation
- **3.** Actuarial modelling use cases
- 4. Insurance use cases
- 5. Al strategy in your business
- 6. Governance framework example
- 7. Next steps



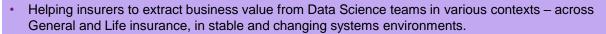
Our Data Science consulting practice

Extracting real business value from data science requires the right combination of technology, culture and insurance domain expertise

About us

- Our Data Science consulting practice is a team of Data Science experts with practical experience of successfully deploying machine learning and AI techniques within an insurance context.
- By collaborating with the WTW consulting teams, we provide a unique combination of technical Data Science delivery with domain expertise and industry experience.

Best practice review and roadmap development



The creation of Data Science sophistication roadmaps, by carrying out best practice reviews of the existing technology and capability.

Infrastructure design

Supporting insurers with integrating Data Science tools and platforms with existing insurance processes & systems, identifying and recommending operating model changes to increase efficiency and reduce risk of errors.

Data Science delivery

Working with insurers to identify the use cases across various teams, carrying out the analytics to identify opportunities and deploying the analytics into production to extract business value.

Case studies

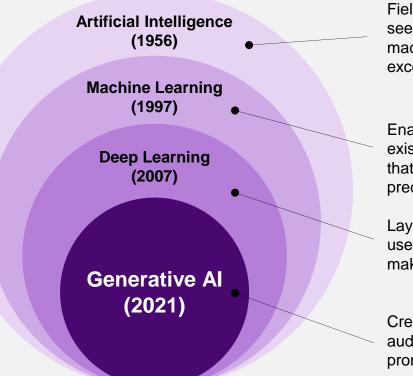
Integrating Data Science

- We have worked with an insurer to develop a blueprint for future best practice modelling.
- The project included a specific focus on how best to embed machine learning and traditional modelling techniques together, and on how to ensure the insurer could leverage the maximum possible advantage from Data Science but within its current implementation constraints.
- Our work included specific support to upskill and develop the team with teaching and training around best practice modelling.
- Working with WTW allowed the insurer to embed machine learning successfully within the teams, in such a way that optimally combined the strengths of the various technologies currently available to the insurer.

Improving customer experience

- A large UK insurer was experiencing issues with an increasing lapse rate over time. The client was unable to identify the source of the issue.
- WTW conducted an initial discovery exercise, working with the analysts, call handlers and senior stakeholders to understand the existing processes.
- Historical data was analysed using Data Science techniques, and the drivers of the observed lapse rate increase over time were identified.
- The core issue was identified and this. combined with other recommendations from WTW such as outgoing communications, allowed the insurer to not only reduce lapse rates to previous levels, but also provided insight on how to reduce this further.

Why all the hype now? Much of the 2023 excitement relates to Generative AI

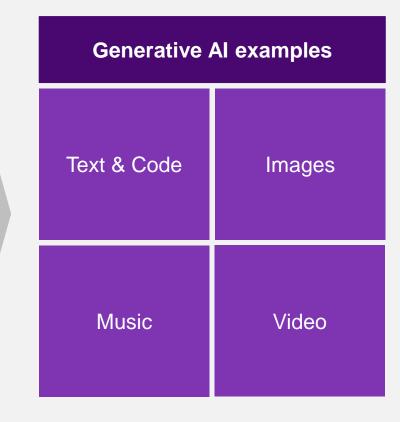


Field of computer science that seeks to create intelligent machines that can replicate or exceed human intelligence

Enables machines to learn from existing data and improve upon that data to make decisions or predictions

Layers of neural networks are used to process data and make decisions

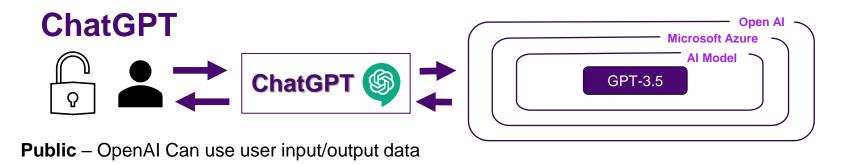
Create new written, visual and auditory content given prompts.

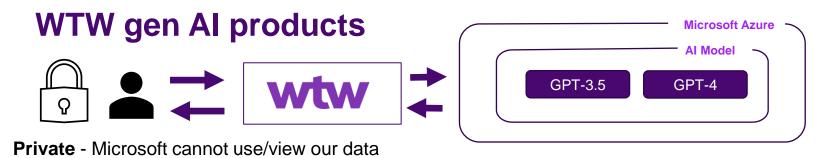


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AI terminology overview

Generative AI	A group of AI models which generate both text (GPT- 4) and images (mid-journey/ Dalle-2)	GPT 3 / 3.5 / 4	Different types of GPT models: GPT-3.5 is an updated to GPT-3 and powers ChatGPT, GPT-4 is 10 times more advanced and therefore much more powerful and expensive	
Large Language Models	Generative AI models trained on huge amounts of text and data, for example GPT-4 and Llama	GFT 37 3.37 4		
GPT	Generative Pretrained Transformer, a type of AI model which produced high quality text	ChatGPT	A customer facing website in a chatbot form that uses GPT-3.5 to respond to prompts	







Strengths and limitations



LLMs excel at generating text that closely resembles text written by humans



These models are competent at solving novel unseen problems



LLMs can be biased based on the data it has been trained on



LLMs can very confidently generate incorrect answers



LLMs make use of additional context to inform their responses



LLMs can be finetuned for specific tasks and behaviors



LLMs can struggle with arithmetic and computational tasks

Risks and threats

Solved problems / Trivial risks

- Hallucinations / Unpredictable behaviours
 - reduced with RAG and more sophisticated models
- Bias / Toxicity
 - Mostly an issue with customer facing systems
- Data / IP leakage
 - Firewalled private models
- Copyright ownership of training datasets
 - Google / Microsoft are taking legal responsibility

Real problems / Potential risks

- Over-reliance
 - erosion of understanding, especially among junior colleagues
- Job security and reskilling
 - Marginal cost of expertise falls to zero
- Ignoring AI
 - Competitors will be utilising these technologies

Regulatory perspectives from the European Union

European Legislation has been geared towards AI developments since 2019, supporting a EU-wide approach to AI. Common themes across the discussions, research publications and proposals are to establish a high degree of trustworthiness, accountability and transparency in the use of AI, with a strong focus on human oversight. So far, the European Commission has released:



INDEPENDENT HIGH-LEVEL EXPERT GROUP ON ARTIFICIAL INTELLIGENCE SET UP BY THE EUROPEAN COMMISSION ETHICS GUIDELINES FOR TRUSTWORTHY AI

The White Paper specifically considered the training data, maintaining records of the data sets used for training, and overarching human oversight to ensure systems do not undermine human autonomy or lead to other unintended consequences. The guidelines emphasize the importance of developing AI systems in a trustworthy and responsible manner, stressing that they should be designed around transparency, fairness and accountability.



The proposed regulation focuses heavily on 'high-risk' AI systems, and strongly considers consistency with existing policy provisions in areas of overlap, such as data – in fact this is designed to complement the provisions of the GDPR itself.

Regulatory perspectives from the USA and the UK

Kathleen Birrane (chair of National Association of Insurance Commissioners' (NAIC) Innovation, Cybersecurity, and Technology committee):

"This touches every area of insurance in one way or another ... the risks that exist with respect to its use are scary."

On discrimination: "AI technology is subject to the same stringent requirements that other insurance practices might be ... I don't care if you use an abacus or the most amazing bright shiny model, what I care is that when you pay somebody, you follow the rules in the output and the end result."

www.insuranceerm.com/analysis/exciting-and-scary-the-insuranceregulators-view-on-ai.html





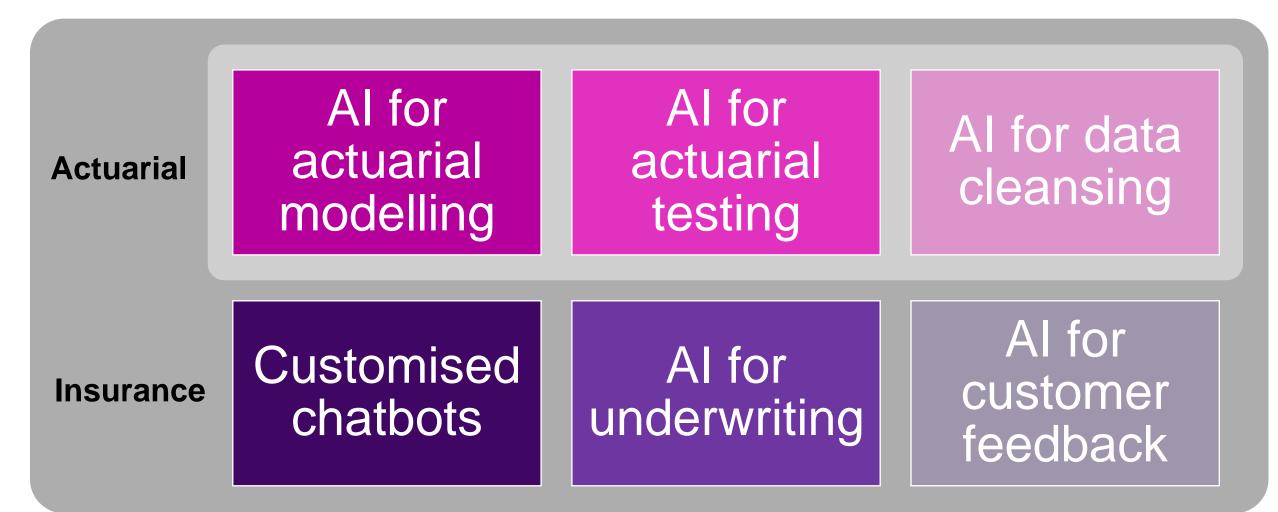
The UK Government published its AI White Paper in 2023, setting out its proposals for regulating the use of artificial intelligence (AI) in the United Kingdom. The White Paper is a continuation of the AI Regulation Policy Paper which introduced the UK Government's vision for the future "pro-innovation" and "context-specific" AI regulatory regime in the United Kingdom.

The White Paper proposes a different approach to AI regulation compared to the EU's AI Act. Instead of introducing a new far-reaching legislation to regulate AI in the United Kingdom, the UK Government is focusing on setting expectations for the development and use of AI alongside empowering existing regulators like the Information Commissioner's Office (ICO), the Financial Conduct Authority (FCA), and Competition and Markets Authority (CMA) to issue guidance and regulate the use of AI within their remit.

Use cases

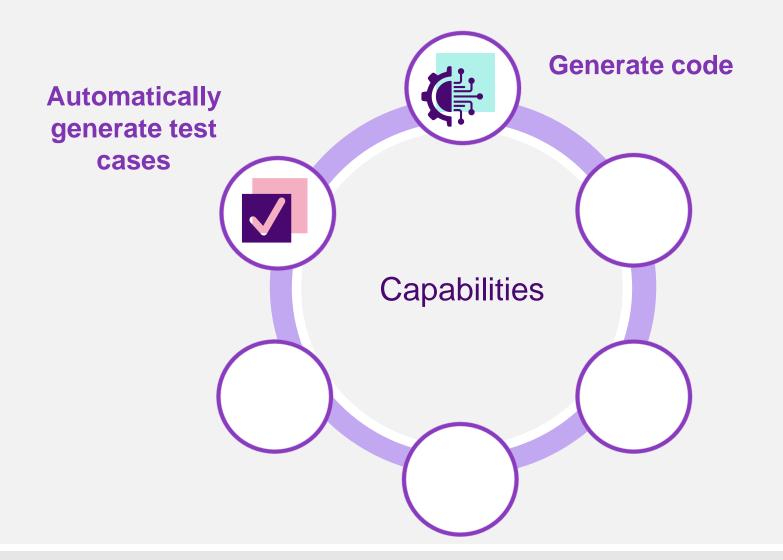


Gen AI use in insurance



Modelling use case #1: AI for actuarial modelling

What AI coding assistants can do right now





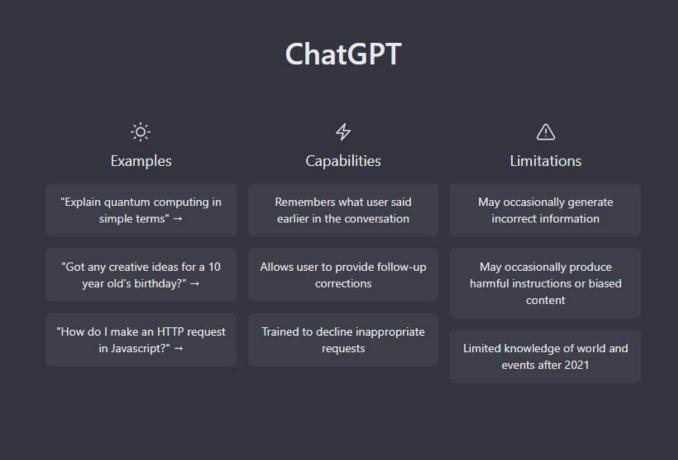
Generate code

 Given a natural language prompt of user requirements, the bot will be able to generate the code that fulfils these requirements

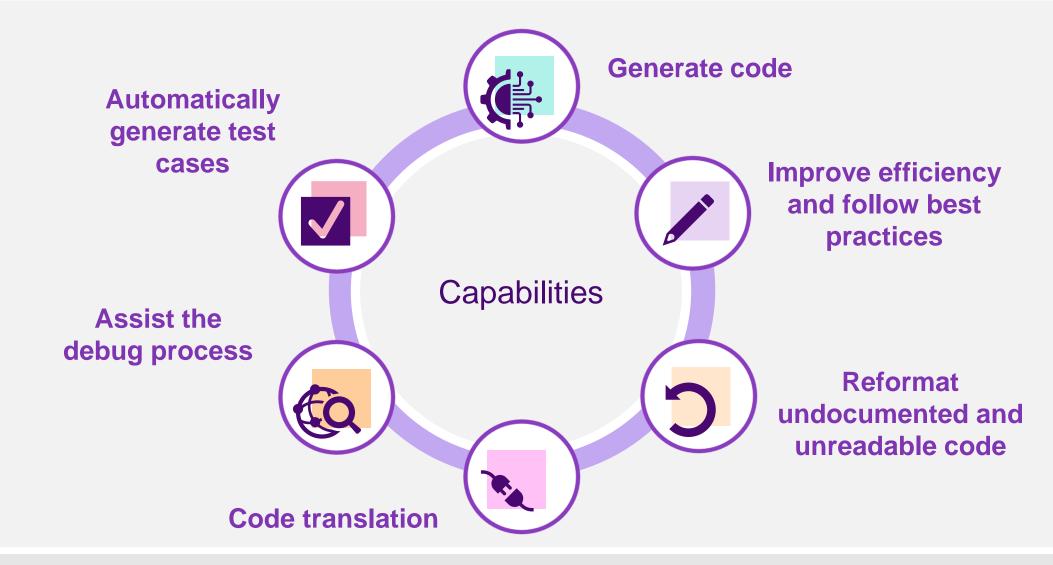


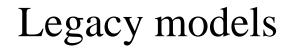
Automatically generate test cases

 Given a function, the bot will auto-generate parameter data for test cases



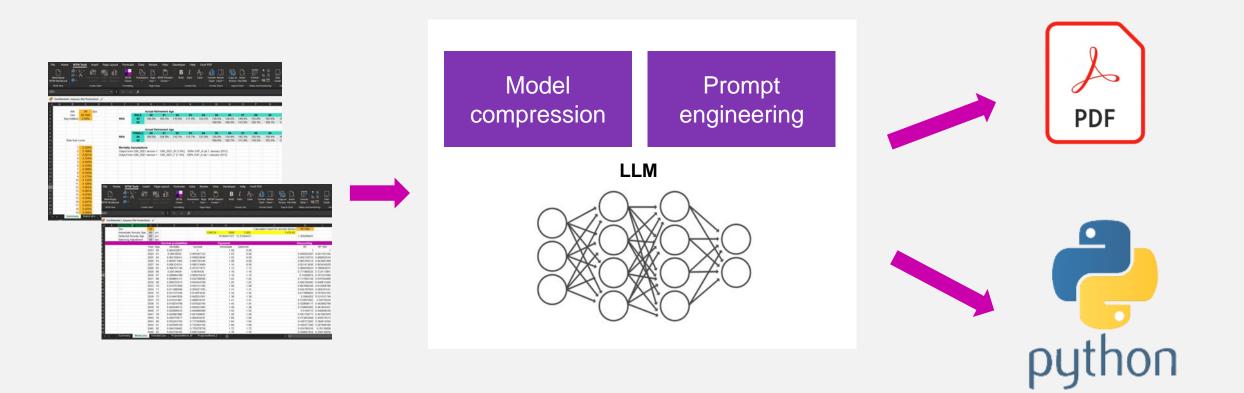
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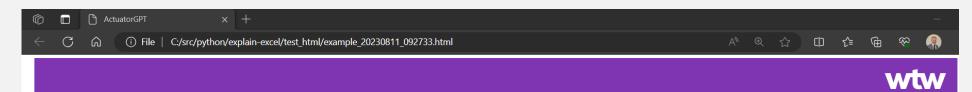


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25 exp_ren_fix 20 20 0.000471277 0.000235611 0 26 exp_ren_mulpilers 100 21 0.00567 0.000471277 0.000235611 0 27 inff_rate_expenses 0 22 0.00567 0.000471277 0.000235611 0 28 decrem Y 23 0.00567 0.000471277 0.000235611 0	0.999528945 0.999764445 0.999528945 0.999764445	-0.000416141 0.00 -0.000416135 0.00	0.00 0.00
26 exp_ren_multipliers 100 21 0.00567 0.000471277 0.000236511 0 27 infl_trate_expenses 0 22 0.00567 0.000471277 0.000235611 0 28 decrem Y 23 0.00567 0.000471277 0.000235611 0	0.999528945 0.999764445	-0.002815589 0.00	101.84 0.00
28 decrem Y 23 0.00567 0.000471277 0.000235611 0	0.999528945 0.999764445	-0.000416123 0.00	0.00 0.00
	0.999528945 0.999764445 0.999528945 0.999764445	-0.000416117 0.00 -0.002815457 0.00	0.00 0.00
	0.999528945 0.999764445	-0.000416104 0.00	0.00 0.00
	0.999533915 0.99976693	-0.000411706 0.00	0.00 0.00
31 do data validation Y 26 0.00561 0.000266302 0.000233124 0 → Data Assumptions Calc RAFM Output Comparison < Match> (←)	0.999533915 0.99976693	-0.002904298 0.00	106.92 0.00

Using generative AI to assist transformation



Generation of an audit trail or summary report



Excel Workbook: late_retirement_factors.xlsm

Workbook Summary

This workbook is made up of three sheets: Summary, MaleCalcs, and FemaleCalcs. The Summary sheet provides an overview of the calculations for male and female late retirement factors based on different ages and interest rates. The MaleCalcs and FemaleCalcs sheets perform the calculations for males and females, respectively, using mortality assumptions and interest rates.

Summary Sheet

The Summary sheet displays the late retirement factors for males and females based on different ages and interest rates. The sheet retrieves data from the MaleCalcs and FemaleCalcs sheets and presents it in a tabular format. The interest rates used in the calculations are provided in column C, ranging from C12 to C88. The sheet also contains some key numerical assumptions, such as the average inflation rate of 2.5% (cell C4) and the risk-free curve (cell F10).

MaleCalcs Sheet

The MaleCalcs sheet calculates the late retirement factors for males using mortality assumptions and interest rates. The sheet uses the INDEX and MATCH functions to retrieve mortality rates from the ProjectedMort_M sheet based on the age and year. It then performs calculations for immediate and deferred annuity factors using the interest rates from the Summary sheet. The results are displayed in columns Z to AT for different ages and interest rates.

FemaleCalcs Sheet

The FemaleCalcs sheet calculates the late retirement factors for females using mortality assumptions and interest rates, similar to the MaleCalcs sheet. It retrieves mortality rates from the ProjectedMort_F sheet and performs calculations for immediate and deferred annuity factors using the interest rates from the Summary sheet. The results are displayed in columns Z to AT for different ages and interest rates.

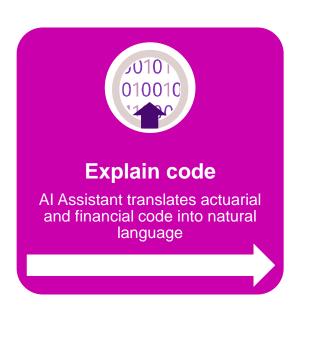
VBA Code

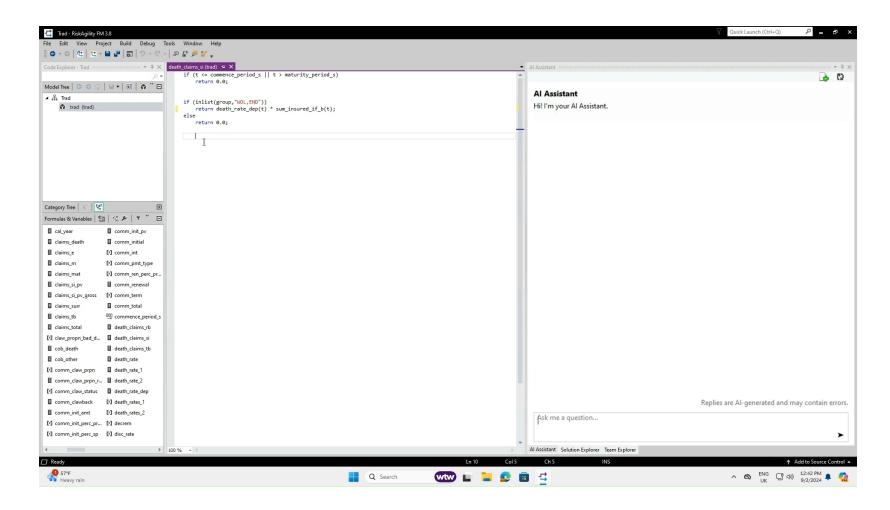
Generation of python code

```
explain_excel.ipynb
                      🕏 example_1686065389.py 1
                                                  example_1686127655.py ×
test_py > 🔹 example_1686127655.py > ...
       import pandas as pd
  1
       def annuity factors(
               sex, age, immediate annuity age, deferred annuity age, ir curve, ma adjustment, mort m filepath,
               mort f filepath, mort m sheetname, mort f sheetname
               ):
           mort m = pd.read excel(mort m filepath, mort m sheetname, header=10, index col=1)
           mort f = pd.read excel(mort f filepath, mort f sheetname, header=10, index col=1)
           mort = mort m if sex == "M" else mort f
 11
 12
           survival prob = mort.loc[age].values[0]
           immediate payment = 1 if age >= immediate annuity age else 0
           deferred payment = 1 if age >= deferred annuity age else 0
           discount rf = (1 + ir curve) ** (-age)
           discount rf ma = (1 + ir_curve + ma_adjustment / 10000) ** (-age)
           annuity factor rf = survival prob * immediate payment * discount rf
           annuity factor rf ma = survival prob * deferred payment * discount rf ma
           return annuity_factor_rf, annuity_factor_rf_ma
```

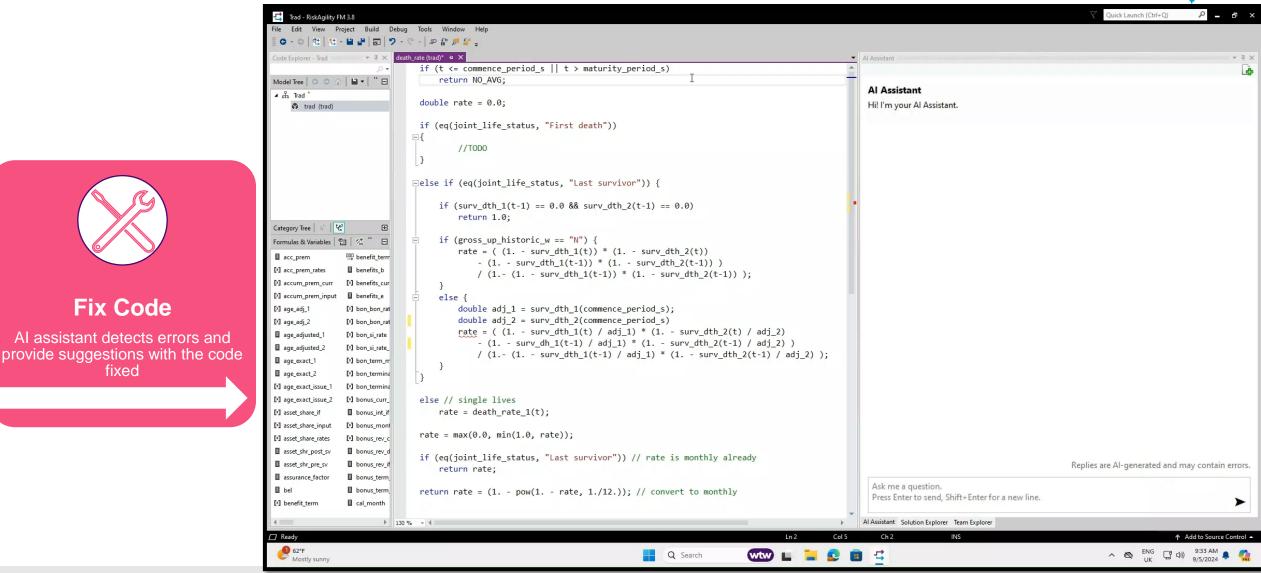
Prompt: Please explain the code I have selected







Prompt: There is a problem with the selected code, fix it for me.



Fix Code

fixed

Prompt: Can you write the code for a join_life_status equal to "First Death" using death rate for life 1 and life 2



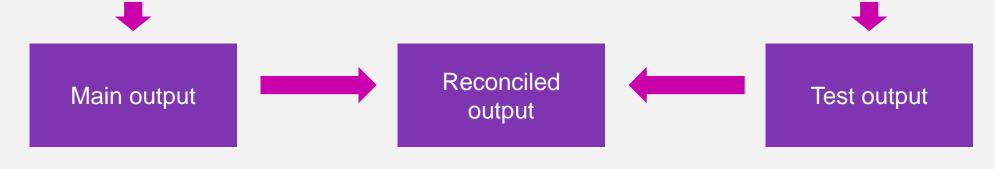
iode Explorer - Trad 🕬 🐨 🔻 🕇 🗙		Al Assistant T
eath 🗙 👻	<pre>if (t <= commence_period_s t > maturity_period_s)</pre>	
1odel Tree 🗢 🗢 🏠 🗎 🕶 🦈 🖂 🖂	return NO_AVG;	AI Assistant
🛱 Trad 🗘 trad (trad)	double rate = 0.0;	Hi! I'm your Al Assistant.
	<pre>if (eq(joint_life_status, "First death"))</pre>	
	{	
	//TODO	
	}	
	<pre>else if (eq(joint_life_status, "Last survivor")) {</pre>	
	if (surv_dth_1(t-1) == 0.0 && surv_dth_2(t-1) == 0.0)	
	return 1.0;	
Category Tree 😤 🛛 🕑		
ormulas & Variables 🕲 🎋 🍈 日	<pre>if (gross_up_historic_w == "N") {</pre>	
claims_death	rate = ((1 surv_dth_1(t)) * (1 surv_dth_2(t)) - (1 surv_dth_1(t-1)) * (1 surv_dth_2(t-1)))	
cob_ <mark>death</mark>	$/ (1 (1 surv_dth_1(t-1)) * (1 surv_dth_2(t-1)));$	
death_claims_rb	}	
death_claims_si	else {	
death_claims_tb	<pre>double adj_1 = surv_dth_1(commence_period_s);</pre>	
death_rate	<pre>double adj_2 = surv_dth_2(commence_period_s);</pre>	
death_rate_1	rate = ((1 surv_dth_1(t) / adj_1) * (1 surv_dth_2(t) / adj_2) - (1 surv dth 1(t-1) / adj 1) * (1 surv dth 2(t-1) / adj 2))	
death_rate_2	/ (1 surv_dth_1(t-1) / adj_1) * (1 surv_dth_2(t-1) / adj_2));	
death_rate_dep	}	
x] death_rates_1	}	
death_rates_2		
policy_deaths	else // single lives	
surplus_sh_death	<pre>rate = death_rate_1(t);</pre>	
	rate = max(0.0, min(1.0, rate));	
	<pre>if (eq(joint_life_status, "Last survivor")) // rate is monthly already return rate;</pre>	Replies are Al-generated and may contain erro
	return rate = (1 pow(1 rate, 1./12.)); // convert to monthly	Ask me a question. Press Enter to send, Shift+Enter for a new line.
	130 % ~ 4	Al Assistant Solution Explorer Team Explorer

Modelling use case #2: AI for actuarial testing

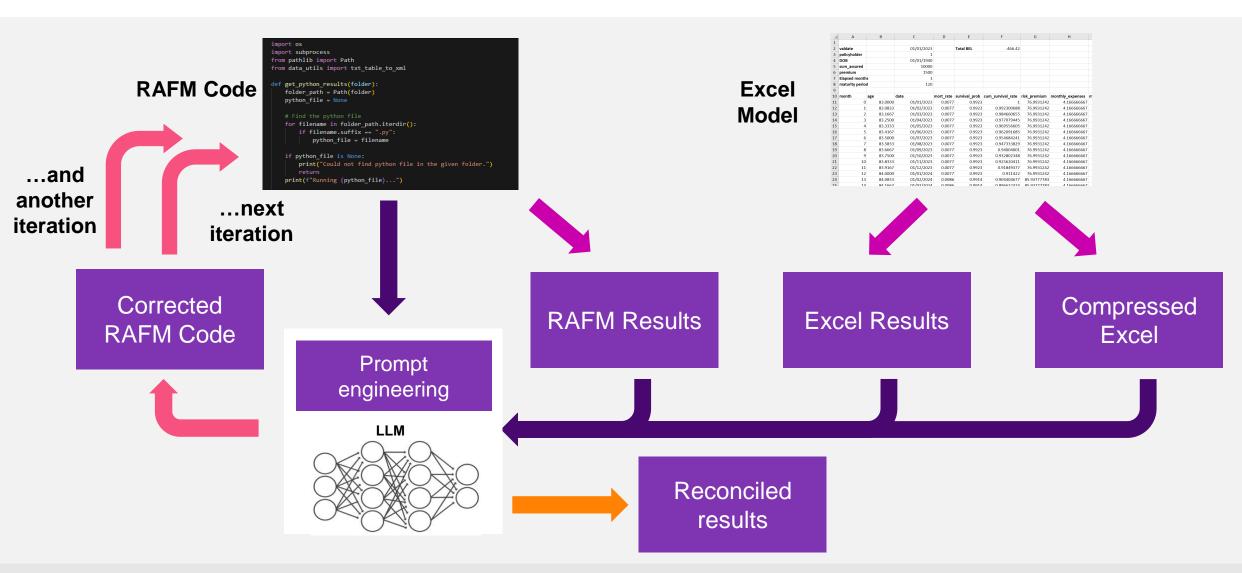


Model reconciliation is a manual and time-consuming process

simple_cashflow.py ×	_									
		A		В	С	D	E	F	G	Н
auto_recon > test_files > test2 > 🌩 simple_cashflow.py > 🎯 cashflow_model	1									
1 import pandas as pd	2	valdate			01/01/2023		Total BEL	-466.42		
2 import numpy as np	3	policyholder			1					
3 from datetime import datetime	4	DOB			01/01/1940					
4 import os	5	sum_assured			10000					
5 import shutil	6	premium			1500					
6	7	Elapsed month	is		1					
7	8	maturity perio	d		120					
8 def datedif_years(date1, date2):	9									
9 years = date2.year - date1.year			age		date n	nort rate	survival prob	cum survival rate	risk premium	monthly_expenses m
<pre>10 if (date2.month, date2.day) < (date1.month, date1.day):</pre>	11		-	83.0000	01/01/2023	0.0077			76.9931242	
11 years -= 1	12			83.0833	01/02/2023	0.0077				
12 return years	13			83.1667	01/03/2023	0.0077				
13	14			83.2500	01/04/2023	0.0077				
14	4.5			83.3333	01/05/2023	0.0077			76.9931242	
15 def cashflow_model(valdate, policyholder, dob, sum_assured, premium, elapsed_months, maturity_peri	10 15			83.4167	01/06/2023	0.0077			76.9931242	
<pre>16 data = pd.read_excel(excel_workbook_path, sheet_name="data", index_col=0)</pre>	10									
17				83.5000	01/07/2023	0.0077				
18	18			83.5833	01/08/2023	0.0077				
19 mort_table = pd.read_excel(19			83.6667	01/09/2023	0.0077			76.9931242	
20 excel_workbook_path, sheet_name="assumptions", header=1, nrows=101, index_col=0	20			83.7500	01/10/2023	0.0077				
21)	21			83.8333	01/11/2023	0.0077			76.9931242	
22	22			83.9167	01/12/2023	0.0077	0.9923	0.91849377	76.9931242	4.166666667
22	23	12		84.0000	01/01/2024	0.0077	0.9923	0.911422	76.9931242	4.166666667
	24	13		84.0833	01/02/2024	0.0086	0.9914	0.904404677	85.93777783	4.166666667
	25	1/		8/ 1667	01/03/2024	0 0086	0 991/	0 896632424	85 93777783	1 166666667



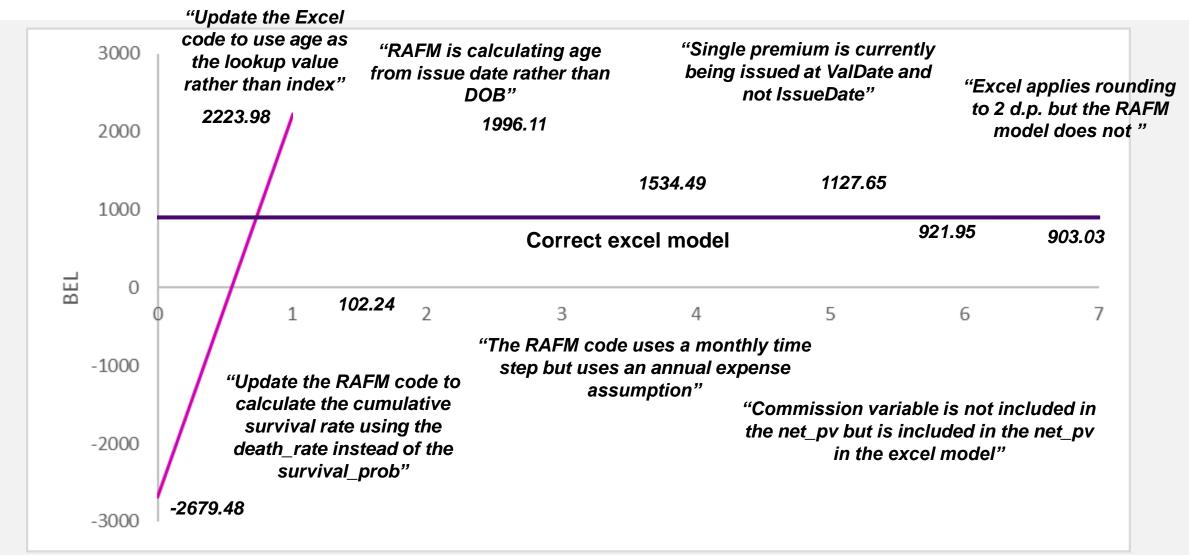
AI for auto-reconciliation





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Self-healing code



Modelling use case #3: AI for data cleansing

Identifying errors, formatting issues, missing values is highly manual

	А	В	С	D	E	F
1	DOB	GENDER	POSTCODE	PRODUCT	MARITAL STATUS	PREMIUM
2	03/01/1994	F	CM12 0HD	PROD3	Single	3867.2
3	13/01/1948	Male	OX9 2BN	PROD2	Yes	3634.07
4	15/01/2002	Female	E15 3LN	1	Single	3847.35
5	12/03/2017	Μ	BH3 7NE	PROD1	Married	3926.7
6	03/11/2020	F	CR44 1AP	PROD2	maried	3781.02
7	30/08/1951	Μ	3311 ER	PROD3	out of wed	MALE
8	04/01/1998	F	PL4 0AL	product 1	S	3919.83
9	06/04/1996	F	TR24 0QB	PROD3	Married	3639.61
10	14/11/1936	U	DH1 4JU	PROD 3	Married	3831
11	Alan	М	GL4 6DG	2	Engaged	4058.26
12	11/02/1990	Μ	LD2 3ND	PROD2	Married	n/a
13	21/04/1974	F		PROD2	no	4275.75
14	31/12/1974	Mr.	LL47 6TW	PROD3	Married	4152.53
15	19/01/1929	F	ME12 3TB	PROD3	not married	"3988.99"
16	14/12/1958	Μ	EH6 4RZ	PROD2	Married	4210.6
17	21/07/1996	male	OX29 4JX	product 2	civil partnership	£4,298.42
18	22/05/1986	Μ	LA2 0PB	PROD2	Single	3879.98
19	02/03/1933	F	24 Barry Lane	PROD3	Married	3587.15
20	23/04/1996	FEMALE	EX31 1JF	PROD3	М	n/a

File Home Shar	e View					
Pin to Quick Copy Paste access Cipboard		and the second second	Rename New folder	s * Properties 🖉 Edit 🔠 Select * With the select test of		
← → + ↑ □ > T	his PC → Win10-v7.	.0-0365x86 (C:) → stc →	gui-resources > data_cleansing		✓ Ŏ ,○ Search data_cleansing	
	his PC > Win10-v7.				V V Search data_cleansing	

Data cleansing process

Raw excel input

	A	В	С	D	E	F
1	DOB	GENDER	POSTCODE	PRODUCT	MARITAL STATUS	PREMIUM
2	03/01/1994	F	CM12 0HD	PROD3	Single	3867.2
	13/01/1948	Male	OX9 2BN	PROD2	Yes	3634.07
4	15/01/2002	Female	E15 3LN	1	Single	3847.35
5	12/03/2017	М	BH3 7NE	PROD1	Married	3926.7
6	03/11/2020	F	CR44 1AP	PROD2	maried	3781.02
	30/08/1951	M	3311 ER	PROD3	out of wed	MALE
8	04/01/1998	F	PL4 0AL	product 1	S	3919.83
9	06/04/1996	F	TR24 0QB	PROD3	Married	3639.61
10	14/11/1936	U	DH1 4JU	PROD 3	Married	3831
11	Alan	М	GL4 6DG	2	Engaged	4058.26
12	11/02/1990	М	LD2 3ND	PROD2	Married	n/a
13	21/04/1974	F		PROD2	no	4275.75
14	31/12/1974	Mr.	LL47 6TW	PROD3	Married	4152.53
15	19/01/1929	F	ME12 3TB	PROD3	not married	"3988.99"
16	14/12/1958	М	EH6 4RZ	PROD2	Married	4210.6
17	21/07/1996	male	OX29 4JX	product 2	civil partnership	£4,298.42
18	22/05/1986	М	LA2 0PB	PROD2	Single	3879.98
19	02/03/1933	F	24 Barry Lane	PROD3	Married	3587.15
20	23/04/1996	FEMALE	EX31 1JF	PROD3	М	n/a

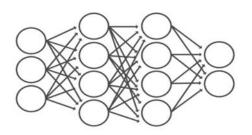
Generate cleaning rules for each column File LangChain GENDER LLM F DOB 03/01/1994

Output python rules





Merge python rules



wtw

Clean excel output

	A	В	С	D	E	F
1	GENDER_origin	GENDER_clea -	GENDER_commer -	POSTCODE_origine	POSTCODE_clea -	POSTCODE_commer -
	F	F	OK	CM12 0HD	CM12 0HD	OK
3	Male	M	CLEANED	OX9 2BN	OX9 2BN	OK
	Female	F	CLEANED	E15 3LN	E15 3LN	OK
	M	M	OK	BH3 7NE	BH3 7NE	OK
	F	F	OK	CR44 1AP	CR44 1AP	OK
	M	M	OK	3311 ER		ERROR
	F	F	OK	PL4 0AL	PL4 0AL	OK
	F	F	OK	TR24 0QB	TR24 0QB	OK
	U		ERROR	DH1 4JU	DH1 4JU	OK
	M	M	OK	GL4 6DG	GL4 6DG	OK
	M	M	OK	LD2 3ND	LD2 3ND	OK
	F	F	OK			BLANK
14	Mr.	M	CLEANED	LL47 6TW	LL47 6TW	OK
	F	F	OK	ME12 3TB	ME12 3TB	OK
16	M	M	OK	EH6 4RZ	EH6 4RZ	OK
	male	м	CLEANED	OX29 4JX	OX29 4JX	OK
18	M	M	OK	LA2 0PB	LA2 0PB	OK
19	F	F	OK	24 Barry Lane		ERROR

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Run python rules



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Python rules generated

```
def clean GENDER(df, column):
   df[column+'_original'] = df[column]
   df[column+'_clean'] = df[column]
   df[column+' comment'] = 'OK'
   male formats = ['Male', 'male', 'M', 'Mr.']
   female_formats = ['Female', 'female', 'F', 'feemale']
   unfixable_errors = ['U', 'Labour', 'Darren']
    for i in df.index:
        try:
           if df.loc[i, column] in male_formats:
               df.loc[i, column+' clean'] = 'M'
               if df.loc[i, column] != 'M':
                   df.loc[i, column+' comment'] = 'CLEANED'
            elif df.loc[i, column] in female formats:
               df.loc[i, column+'_clean'] = 'F'
               if df.loc[i, column] != 'F':
                   df.loc[i, column+' comment'] = 'CLEANED'
            elif df.loc[i, column] in unfixable errors or pd.isnull(df.loc[i, column]):
               df.loc[i, column+' clean'] = ''
               df.loc[i, column+' comment'] = 'ERROR' if df.loc[i, column] in unfixable errors else 'BLANK'
       except Exception as e:
           df.loc[i, column+'_clean'] = ''
            df.loc[i, column+' comment'] = 'ERROR'
            print('Error processing row', i, ':', str(e))
    return df[[column+'_original', column+'_clean', column+'_comment']]
```

Cleansed output

	А	В	С	D	E	F	G	Н	
1 GENDE	ER_origin	GENDER_clea -	GENDER_commer -	POSTCODE_origina	POSTCODE_clea -	POSTCODE_commer -	PRODUCT_origina	PRODUCT_clea -	PRODUCT_commer -
2 F		F	OK	CM12 0HD	CM12 0HD	OK	PROD3	PROD3	OK
3 Male		Μ	CLEANED	OX9 2BN	OX9 2BN	OK	PROD2	PROD2	OK
4 Female	e	F	CLEANED	E15 3LN	E15 3LN	OK	1	PROD1	CLEANED
5 M		Μ	OK	BH3 7NE	BH3 7NE	OK	PROD1	PROD1	OK
6 F		F	OK	CR44 1AP	CR44 1AP	OK	PROD2	PROD2	OK
7 M		Μ	OK	3311 ER		ERROR	PROD3	PROD3	OK
8 F		F	OK	PL4 0AL	PL4 0AL	OK	product 1	PROD1	CLEANED
9 F		F	OK	TR24 0QB	TR24 0QB	OK	PROD3	PROD3	OK
10 <mark>U</mark>			ERROR	DH1 4JU	DH1 4JU	OK	PROD 3	PROD3	CLEANED
11 M		Μ	OK	GL4 6DG	GL4 6DG	OK	2	PROD2	CLEANED
12 M		Μ	OK	LD2 3ND	LD2 3ND	OK	PROD2	PROD2	OK
13 F		F	OK			BLANK	PROD2	PROD2	OK
14 <mark>Mr.</mark>		Μ	CLEANED	LL47 6TW	LL47 6TW	OK	PROD3	PROD3	OK
15 F		F	OK	ME12 3TB	ME12 3TB	OK	PROD3	PROD3	OK
16 M		Μ	OK	EH6 4RZ	EH6 4RZ	OK	PROD2	PROD2	OK
17 <mark>male</mark>		Μ	CLEANED	OX29 4JX	OX29 4JX	OK	product 2	PROD2	CLEANED
18 M		Μ	OK	LA2 0PB	LA2 0PB	OK	PROD2	PROD2	OK
19 F		F	OK	24 Barry Lane		ERROR	PROD3	PROD3	ОК

Generative AI will be in every stage of the modelling life cycle



Insurance use case #1: AI for expert systems

A customised chatbot for insurance

wtw

User Guide

Please begin your query by stating the topic of your query.

Type your query into the input bar at the bottom of the screen. To submit your query either press enter or the submit button below. The bot may take a time to generate its response, so please be patient.

To clear the chat press the clear button.

Hello! How can I assist you today?

Type your message

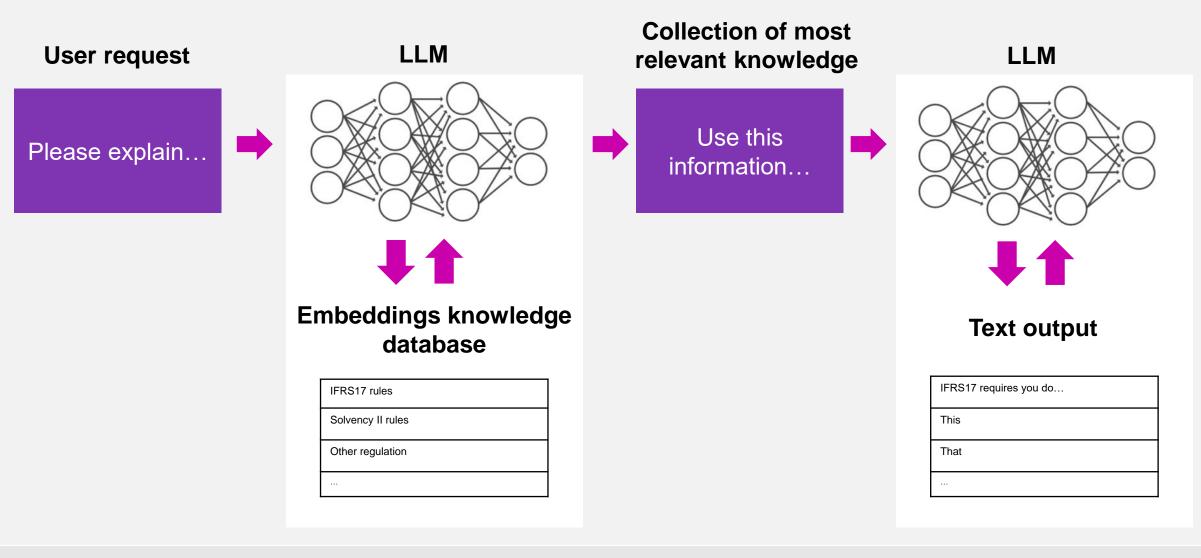
Choose File No file chosen

Submit

Clear

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AI for expert systems



Insurance use case #2: AI for underwriting

Medical records are often messy and unstructured

Personal Health Record

		P	ersonal In	form	ation					
First Name Martha	Last Name Steel			Preferre Mart	ed Name				t Identifier	
Gender F	Date of Birth 10/13/2			Blood T	уре				Ipdated Da	
Address 123 Sample S	treet			City	mple C	ity	State AZ			Zip Code 12345
		E	mergenc	y Coi	ntact					
Full Name Janet Steel		Relati Mot	^{onship} her				act Nur			
^{Full Name} Susan Steel		Relati Sist	onship er				act Nur			
		Ins	surance li	nform	ation					
Insurance Carrier A1 Insurers			ance Plan nprehens	sive F	Plan		act Nur			
Policy Number 12345		Group 123	Number				al Secu 3-45-			
	I		Health Inf	orma	tion					
Physician Informati	on									
Name	Designation/Spec	cialty	Pho	ne		Addr	ess		N	otes
Dr. Max Smith	Family Doctor		555-5555		Fami 26 Sa Terra	ampl		6		
Dr. Ella Lee	Endocrinologi	st	555-5555		Sampl Centre 123 Sa	э,				

		al Informati			
Last Name Date of Birth Steel 10/13/20				Patient Identifier	
			3/2001	ABC123	
	Health	Informatio	n	•	
se	Frequency	Indication		Note	
mg					
	-		2.1.2		
	Type		Date Red		
ooster	Pfizer		June 20	21	
ooster				21	
ooster	Pfizer		June 20	21	
ooster	Pfizer		June 20	21	
ooster	Pfizer		June 20	21	
pooster	Pfizer		June 20	21	
pooster	Pfizer		June 20	21	
pooster	Pfizer		June 20	21	
pooster	Pfizer		June 20	21	
pooster	Pfizer		June 20	21	

Image recognition / Optical character recognition (OCR)

Engline Run analysis Analysis	ze options				o v
	Persona	I Health Re	cord		
	Pers	onal Information			
First Name Martha	Last Name Steel	Preferred Name Martha	Patient lo ABC1		
Gender E	Date of Birth 10/13/2001	Blood Type O-		ated Date	
Address 123 Sample S		Sample	City AZ	Zip Code 12345	
Full Name	Eme	ergency Contact	Contact Number		
Janet Steel	Mother		555-5555		
Full Name Susan Steel	Belationsh	-	Contact Number 555-5555		
Insurance Carrier	Insurance	ance Information	Contact Number		
A1 Insurers		ehensive Plan	555-5555		
Policy Number	Group Num 123	nber	Social Security Numb 123-45-6789	er	
		Ith Information			
Physician Informa					
Dr. Max Smith	Designation/Specialty Family Doctor 555		Address mily Doctors Sample	Notes	
			тасе		
Dr. Ella Lee	Endocrinologist 555	Cen	nple Specialist htre, Sample Road		
					_

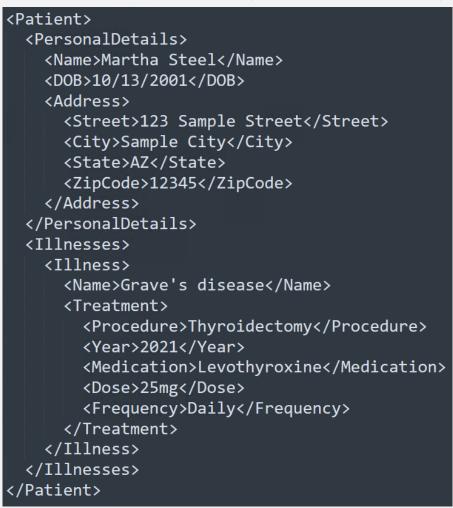
Text Paragraph Personal Health Record Paragraph Personal Information	
Personal Health Record Paragraph Personal Information	
Paragraph Personal Information	
Personal Information	
Paragraph	
First Name	
Paragraph	
Martha	

Using gen AI for summarisation

Raw JSON

son ~		
1 {		
2	"status": "succeeded",	
	"createdDateTime": "2024-01-17T10:06:20Z",	
4	"lastUpdatedDateTime": "2024-01-17T10:06:21Z",	
5	"analyzeResult": {	
6	"apiVersion": "2023-10-31-preview",	
7	"modelId": "prebuilt-read",	
8	"stringIndexType": "utf16CodeUnit",	
9	<pre>"content": "Personal Health Record\nPersonal Informat</pre>	
10	"pages": [Dromot
11	{	Prompt
12	"pageNumber": 1,	engineering
13	"angle": 0.08092603087425232,	engineening
14	"width": 8.2639,	
15	"height": 11.6944,	
16	"unit": "inch",	LLM
17	"words": [
18	{	
19	"content": "Personal",	
20	"polygon": [
21	2.7054,	
22	0.587,	
23	3.7811,	
24	0.5872,	\bigcirc $()$ $()$ $()$ $()$ $()$ $()$ $()$ $()$
25	3.7755,	
26	0.8172,	
27	2.6963,	
28	0.8172	
29],	
30	"confidence": 0.996,	
31	"span": {	
32	"offset": 0,	
33	"length": 8	

Structured XML summary of medical history



Using gen AI for decision-making

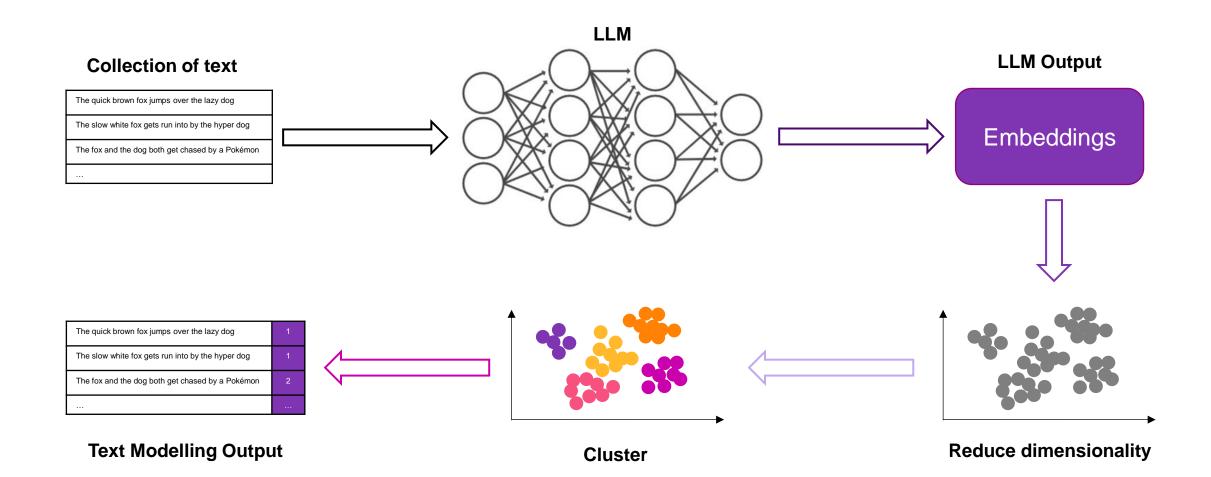
Medical history Prompt engineering <Patient> <PersonalDetails> <Name>Martha Steel</Name> <DOB>10/13/2001</DOB> uw decision template str = """ <Address> <Street>123 Sample Street</Street> You are an AI life insurance underwriter, you make decisions on whether <City>Sample City</City> <State>AZ</State> an application should be rejected or accepeted based on the applicant's <ZipCode>12345</ZipCode> </Address> </PersonalDetails> medical history. Outcome <Illnesses> <Illness> <Name>Grave's disease</Name> Application outcome: <Treatment> Here is the medical history: <Procedure>Thyroidectomy</Procedure> <Year>2021</Year> {medical_history} <Medication>Levothyroxine</Medication> <Dose>25mg</Dose> REJECT <Frequency>Daily</Frequency> </Treatment> Here is the list of illnesses whi </Illness> </Illnesses> {illness df xml} Application outcome explanation: /Patient> You have two tasks **Rejection criteria** The application was rejected because the applicant has a 1) State why the applicant should Α history of Grave's disease, which is listed among the illnesses 2) State the outcome of the appli illness name heartdisease that merit a rejection. Follow the formatting instruction 3 cancer {format_instructions} 4 stroke 11 11 11 alzheimers 5 diabetes 6 gravesdisease Total cost = \$0.015 for summary + \$0.005 for decision = **\$0.02**



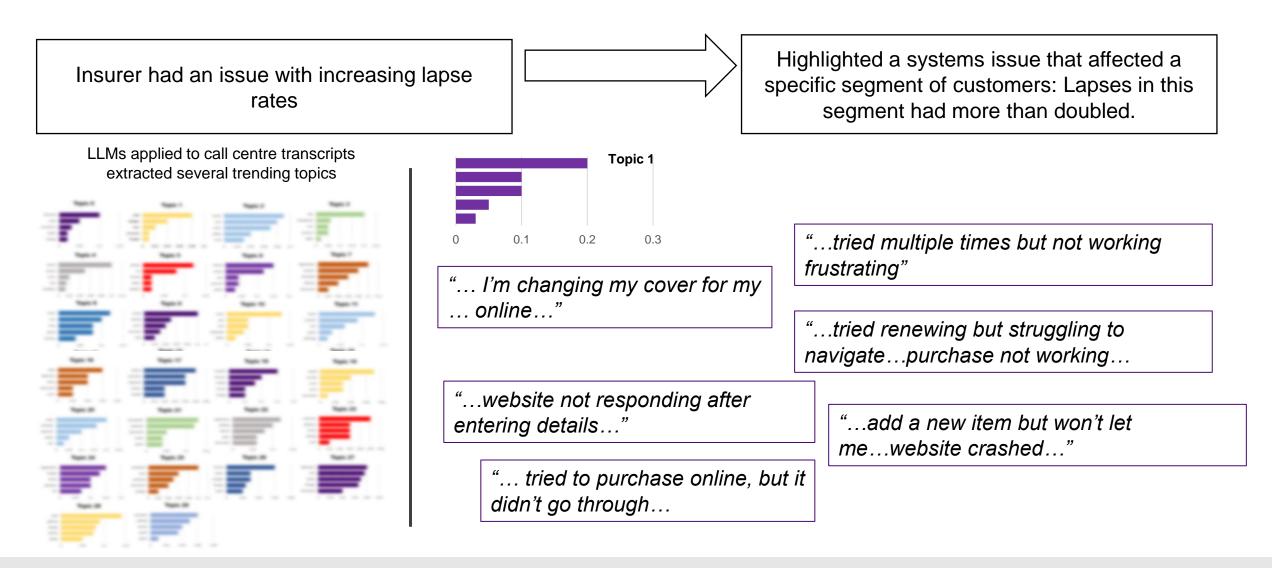
Insurance use case #3: AI for customer feedback



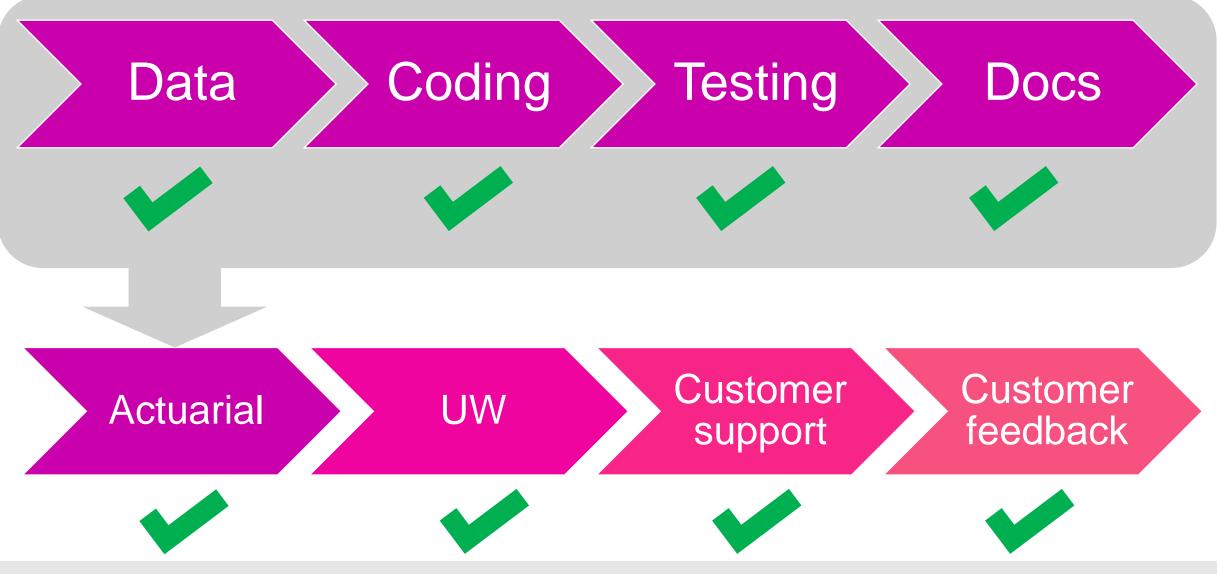
LLMs for topic modelling



Case study: LLMs for topic modelling



Generative AI will be in every stage of the insurance value chain



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AI governance and strategy



AI governance - inputs

Possible model inputs

- Prompts (source code; documents; instructions; chat; scripts; email)
- Any training data provided for model tuning



Don't submit any confidential information, including any personally identifiable information, client data or intellectual property (including source code) to any public AI service intended for personal use (e.g. ChatGPT, Bard).

Don't submit any confidential information, including any personally identifiable information, client data or intellectual property (including source code) to an AI service intended for confidential business use unless you have written evidence of legal review, along with security and business leadership* approval.



Some AI service providers (including business service providers) may inspect, store or use this information to further train models which may violate client contract terms, breach data residency conditions and leak information to other users of the service (this may violate global privacy and wider regulatory requirements resulting in major reputational and financial damage).



Do ensure your legal contact ** confirms the data privacy and data security terms of service are compatible with the intended purpose, and ensure you fully understand service terms and conditions as they apply to inputs.



Do follow standard processes (including security checks and data residency checks) when considering use of a new IT supplier or service providing a generative Al capability. Technology teams may need to update their processes to consider the new risks posed by gen Al.



Do disable any browser option which automatically feeds content of visited web pages to an external AI service.

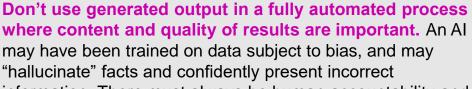
AI governance - outputs

Possible model outputs

- Source code; documents; chat output; scripts; email; web page content)
- Any AI-generated API calls to integrated services (risk models; file search)

Do ensure your legal contact confirms that use of generated output is not restricted by the service provider or other third parties, and there are no thirdparty or service provider ownership rights or access rights on generated output. Ensure you fully understand service terms and conditions as they apply to generated output and service availability characteristics.

Do always get business leadership approval that your use of generative AI output is fit for the intended purpose and risk mitigations are in place.



where content and quality of results are important. An Al may have been trained on data subject to bias, and may "hallucinate" facts and confidently present incorrect information. There must always be human accountability and responsibility for every line of generated output.



×

Do edit Al-generated drafts of client-facing material to conform to internal style guidelines, correct errors, add missing information and delete superfluous information. Making material changes to an AI-generated draft reduces the risk of third-party copyright infringement. An AI may generate content with echoes of copyrighted material used in its training).



Do consciously consider if your company needs to hold the copyright to material, and if so, ensure material improvement or revisions are made to an Al-generated draft. A work generated exclusively by an AI cannot be subject to copyright in some jurisdictions.

AI governance - outputs

Do always treat software elements generated or refactored with the assistance of an AI as third-party code which must be subject to quality, style and security reviews prior to its adoption. A human reviewer must be responsible for and review every line of adopted code and must make any necessary changes to address style, quality, performance or security issues.



Drafts of each generated code instance should be kept to short (tens of lines) fragments in larger works to reduce the risks of copyright infringement and risks of violating licence agreements (including strong copy-left agreements) of software works that may have been part of the training sets of AI models.

Basic guidelines: be sensible

Things you don't need AI for



Things you don't need to develop in-house

What next for gen AI?



The future of gen AI

Customisation

- Your data
- Your preferences

Interactions

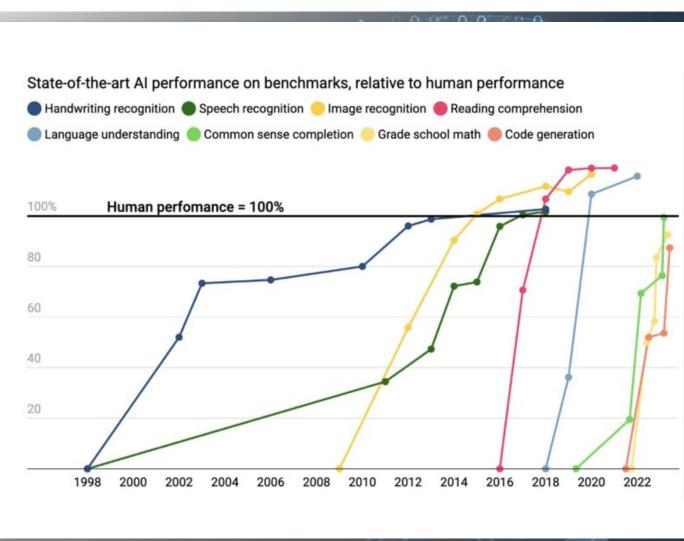
- Tools / plugins
- Copilots

Agents

- Self-prompting
- Autonomy

Improvements

- Faster, cheaper
- Smarter



Next steps

ChatGPT

 Boston Consulting Group saw a 20% uptick in productivity from use of chatbots

Brain-storm

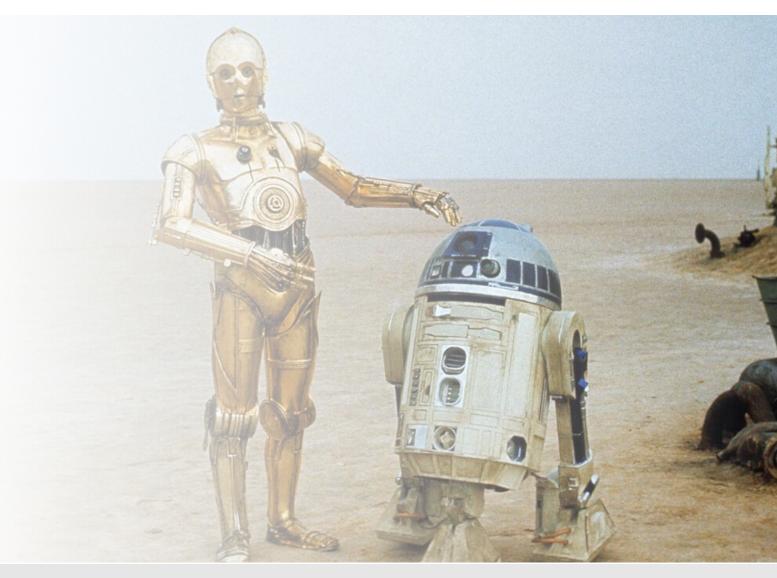
 Organise a focus group in the company to determine where what areas and processes could help the most

AI Steering Committee

 Form a group or name an individual to track developments and establish a company policy or strategy

Stay in touch

• We would love to hear from you about what areas you think would benefit most from these tools and how you are using them in practice



Questions?





