Practical Applications of AI

Focus on Banking

Philippe J.S. De Brouwer

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Defining Artificial Intelligence

Defining Artificial Intelligence

Artificial Intelligence (AI) is not new, however, we are in a critical phase where we have (a) computers that are fast enough to fit large models, and (b) we have enough digital content to allow machines to “learn’ ’.

An important class of AI models rely on learning from pre-defined good answers: “supervised learning.’ ’ For example: we show the AI pictures and tell it when there is a cat in it. The AI learns to recognise pictures with cats. Given enough pictures, it seems like the machine recognises cats just like us.

Classical Algorithms: example linear regression

Definition

The classical algorithms are those where the outcome (fitting of the model) can be done in an analytic formula.

Example

To fit the linear model

$$y = ax + b$$

we optimize $\min_{a,b}\left(\sum_{i=1}^{N}(y_i - \hat{y}_i)^2\right)$

Hence, we can estimate a and b as follows:

$$\hat{a} = \frac{\sigma_{x,y}}{\sigma_x^2} = \rho_{x,y}\frac{\sigma_y}{\sigma_x} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x - \bar{x})^2}$$

$$\hat{b} = \bar{y} - (\hat{a}\bar{x})$$

Linear Regression: visualisation

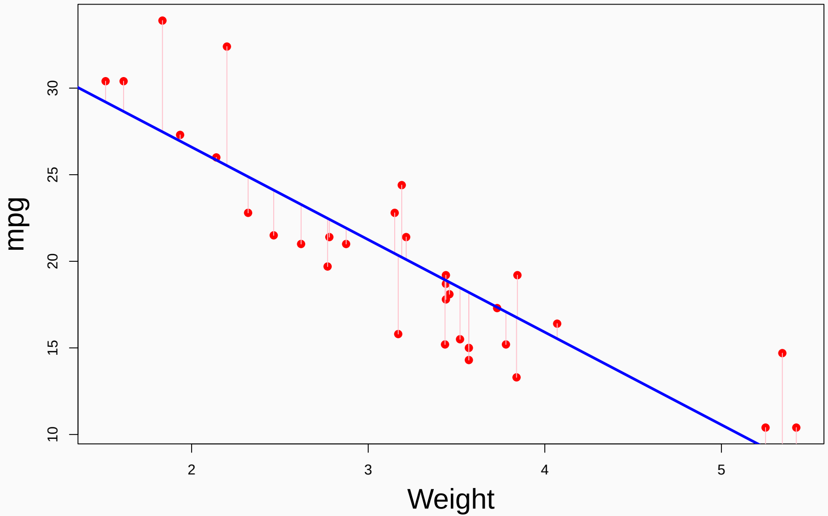


Figure 1: Visualisation of predicting miles per galon with car weight.

Minorities (and other forms of bias)

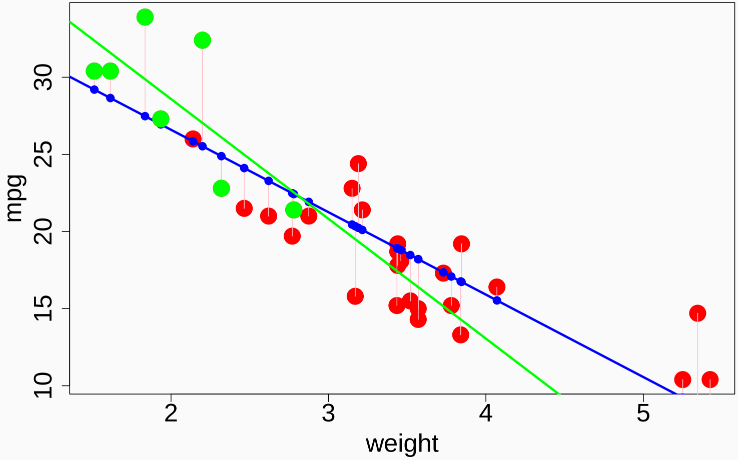
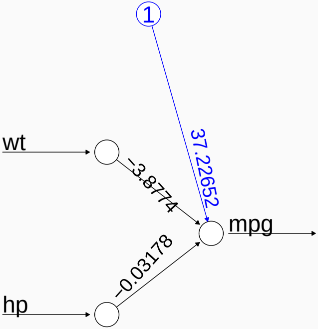


Figure 2: Small city cars (green) see their fuel consumption more over-stated than others and weight influences the consumption more. They are a minority and the model fails to capture their specific nature that is more sensitive to weight.

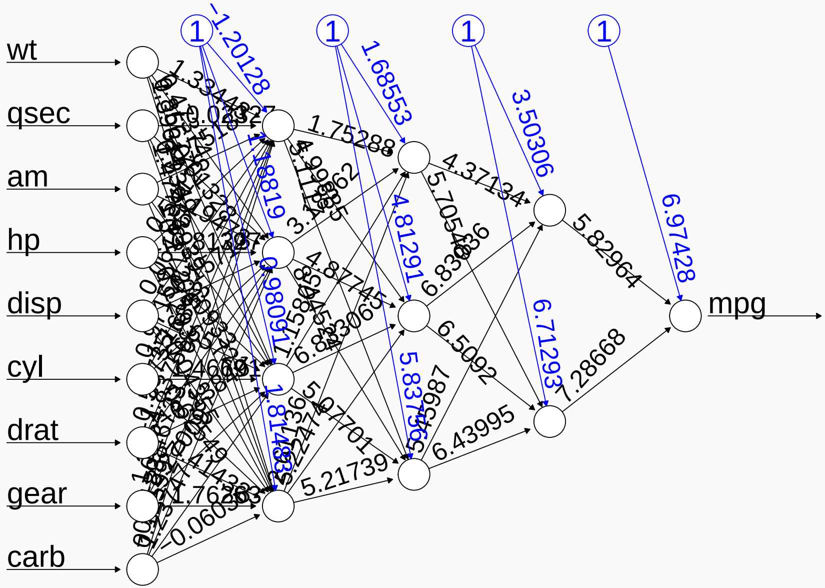
Multiple Linear Regression

$$mpg = a_1 wt + a_2 hp + b$$

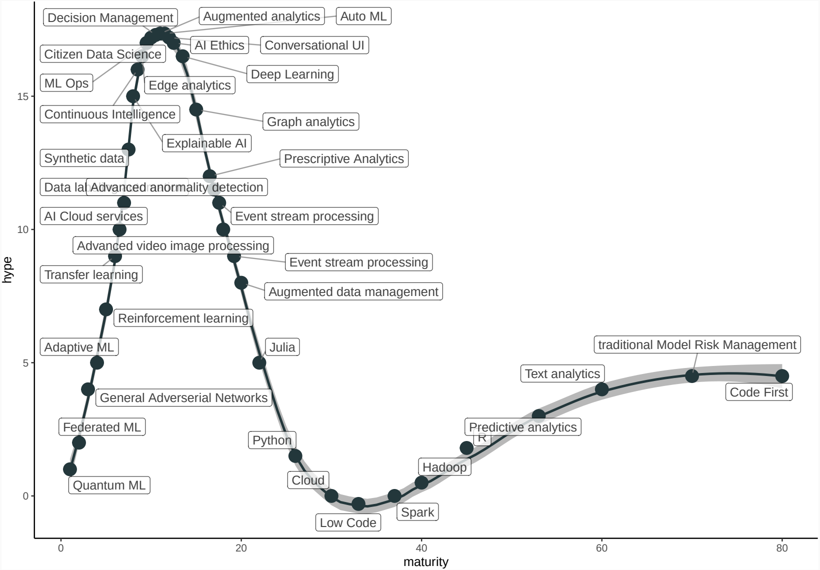
Also the parameters in this model can be calculated exactly and we do not consider this as AI.



Artificial Neural Netwowks



Hype and Maturity



Some Amazing Examples of AI (i): Entire Companies

The success of:

- Netflix
- Google
  - the search engine
  - digital assistant
- Uber
- etc.

Some Amazing Failure of AI (i)

Figure 3: Picture to best knowledge public domain – face-swap gone wrong

Some Amazing Failure of AI (ii): Google

Figure 4: Copy from www.twitter.com.

Some Amazing Failure of AI (iii-a): Google Gemini: Feb 2024

Figure 5: Prompt: "Show me a portrait of the founding fathers of the USA." Image: Gemini..

Some Amazing Failure of AI (iii-b): Google Gemini: Feb 2024

Figure 6: Prompt: "Generate an image of a 1943 German Soldier." Image: Gemini.

The price of built-in racism

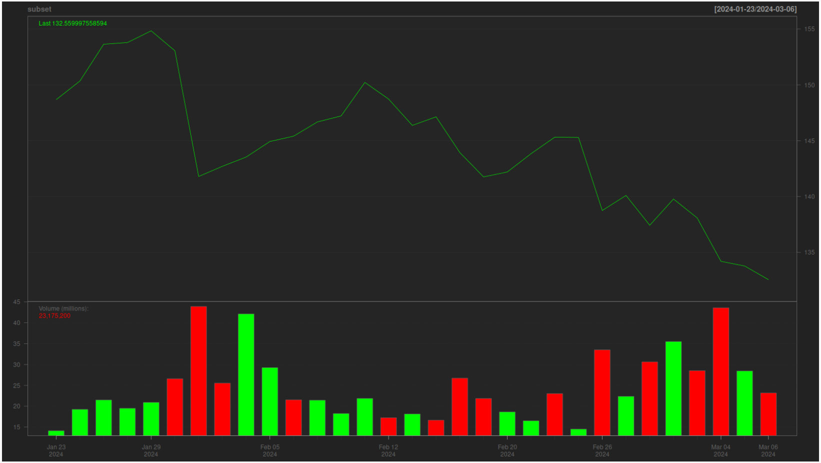


Figure 7: The shares lost USD20, and with 12.46 Billion shares, this is about 249.2 Billion USD market cap destroyed in 2 weeks time.

Today's pearls of Google's persistent racism

Figure 8: Google cancelled the capability to generate images of their racist engine, however it can still find images – retrieved 2023-03-08.

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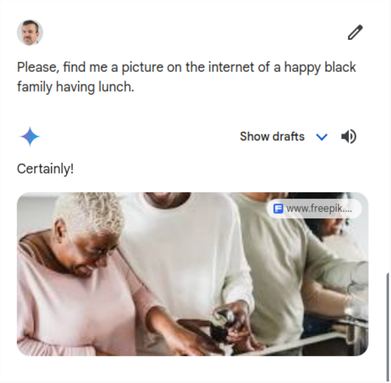
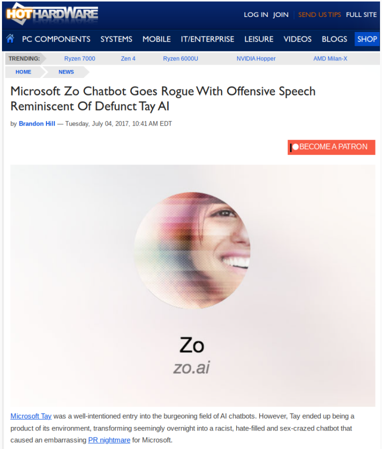


Figure 8: Google cancelled the capability to generate images of their racist engine, however it can still find images – retrieved 2023-03-08.

Some Amazing Failure of AI (iv): Microsoft

Figure 9: Copy from www.twitter.com.

Some Amazing Failure of AI (v): Microsoft a year later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PC COMPONENTS SYSTEMS MOBILE IT/ENTERPRISE LEISURE VIDEOS BLOGS SHOP

TRENDING: Ryzen 7000 Zen 4 Ryzen 6000U NVIDIA Hopper AMD Milan-X

HOME NEWS

Microsoft Zo Chatbot Goes Rogue With Offensive Speech Reminiscent Of Defunct Tay AI

by Brandon Hill — Tuesday, July 04, 2017, 10:41 AM EDT

BECOME A PATRON

Zo
zo.ai

Microsoft Tay was a well-intentioned entry into the burgeoning field of AI chatbots. However, Tay ended up being a product of its environment, transforming seemingly overnight into a racist, hate-filled and sex-crazed chatbot that caused an embarrassing PR nightmare for Microsoft.

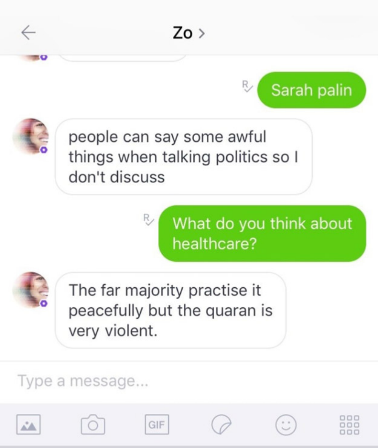


Figure 10: Copy from https://hothardware.com/news/microsoft-zo-chatbot-goes-rogue-with-offensive-speech-tay-ai.

Some Amazing Failure of AI (vi): Impact on Real life

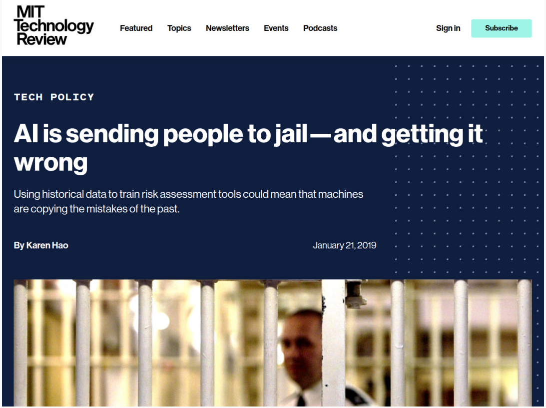


Figure 11: Source: https://www.technologyreview.com/2019/01/21/137783/algorithms-criminal-justice-ai/

Examples: healthcare diagnostics, school outcome, etc.

Some Amazing Failure of AI (vii): More on COMPAS

A computer program used for bail and sentencing decisions was labeled biased against blacks. It's actually not that clear.

By Sam Corbett-Davies, Emma Pierson, Avi Feller and Sharad Goel

October 17, 2016 at 5:00 a.m. EDT

Figure 12: Source: https://www.washingtonpost.com/news/monkey-cage/wp/2016/10/17/can-an-algorithm-be-racist-our-analysis-is-more-cautious-than-propublicas/

Generative AI and Large Language Models

Large Language Models

Now imagine an ANN trained on all texts digitally available. Such model will have many internal layers and billions of parameters. The AI is trained to predict the next word (auto-regressive) or missing word (masked learning). Used in sequence this method creates sentences.

Allow the AI to learn on the data (unsupervised learning), and add some fine tuning (people providing the right answers and call this RHLF (reinforced learning from human feedback)).

Congratulations, you have imagined a large language model (LLM)!

Generative AI

You also heard the term "generative AI' '. Well, that is the wider term for AI that is able to be creative in the sense that it can create things that didn't exist before. Well-known examples are structural design elements, images, and text (the LLMs).

An AI that generates pictures will be constructed and trained differently than an AI that provides conversations, but the basic principles are the same.

Emergent Abilities

LLMs might acquire the ability to do something that they are not trained for. Given a critical level of complexity, they just can do it.

For example, LLMs seem to be able to speak Hinglish (combined English and Hindi), without being trained for it. Other emergent abilities are passing college-level exams, do multi-step arithmetic, identify the intended meaning of a word out of the context, etc.

Note: Emergent Abilities

Already now, in the infancy of AI, we have models that display "emergent abilities": they can do things that they weren't really taught to do.

Hallucinations

Sometimes the LLM will confidentially assert something that does not follow from the data.

For example without fine tuning, most LLMs will answer “no” to the question “Can I teach an old dog new tricks.” This is because of the popular expression “One cannot teach an old dog new tricks?” or

Note: hallucinations

LLMs can “hallucinate”: they can make mistakes or show bias even when the data does not really have that mistake or bias. Those mistakes appear without warning!

Some Amazing Examples of gen.AI (i): Dall.E

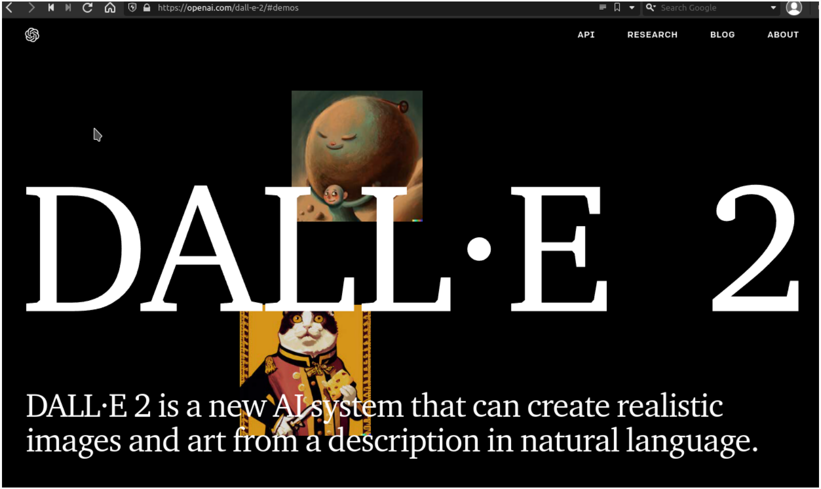


Figure 13: https://openai.com

Some Amazing Examples of AI (ii): ChatGPT

USER **this code is not working like i expect — how do i fix it?**

```
resultWorkerErr := make(chan error)
defer close(resultWorkerErr)
go func() {
        defer cancel()
        resultWorkerErr <- b.resultWorker(ctx)
}()

err := b.worker(ctx)
cancel()
if err == nil {
        return <-resultWorkerErr
}
return multierror.Append(err, <-resultWorkerErr)
```

CHATGPT It's difficult to say what's wrong with the code without more context. Can you provide more information about what the code is supposed to do and what isn't working as expected? Also, is this the entire code or just a part of it?

USER **just part of it — the error never surfaces. I think there is something wrong with the channel**

CHATGPT It's difficult to say without more information about what the code is supposed to do and what's happening when it's executed. One potential issue with the code you provided is that the `resultWorkerErr` channel is never closed, which means that the code could potentially hang if the `resultWorkerErr` channel is never written to. This could happen if `b.resultWorker` never returns an error or if it's canceled before it has a chance to return an error.

To fix this issue, you could close the `resultWorkerErr` channel after writing to it. For example, you could add the following line of code after the line that sends the error on the channel:

```
close(resultworkerErr)
```

Figure 14: https://openai.com – https://chat.openai.com/chat

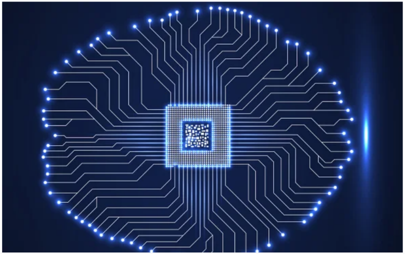
Some Amazing Examples of AI (iii): Research

ARTIFICIAL INTELLIGENCE

AI Generates Hypotheses Human Scientists Have Not Thought Of

Machine-learning algorithms can guide humans toward new experiments and theories

By Robin Blades on October 28, 2021



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Anil Ananthaswamy

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A Deep Dive into Deep Learning
Peter Bruce

ENGINEERING
Demystifying the Black Box That Is AI
Ariel Bleicher

Figure 15: https://www.scientificamerican.com/article/ai-generates-hypotheses-human-scientists-have-not-thought-of/

Some Amazing Examples of AI (iv): Creative Design

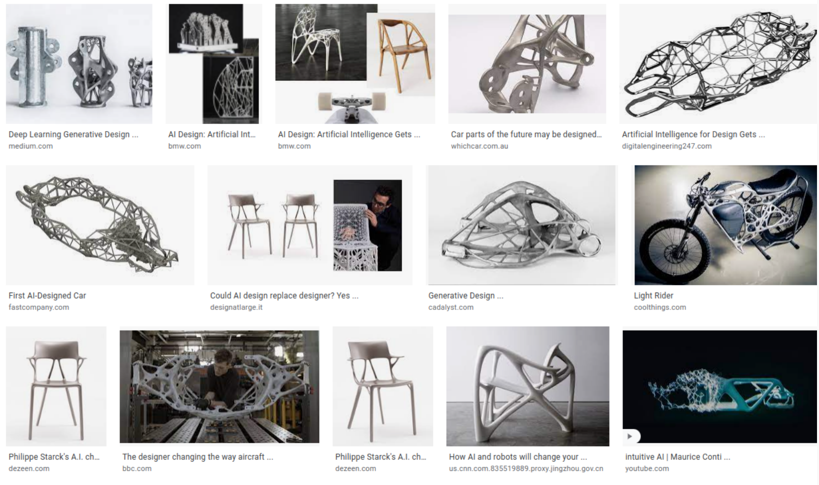

Figure 16: search on www.google.com "AI designed"

Practical Applications of AI

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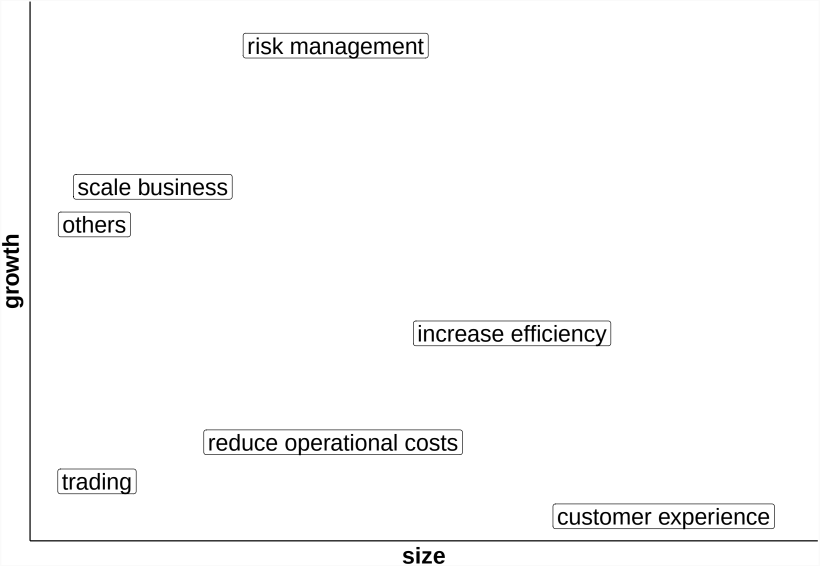
Banking Applications of AI



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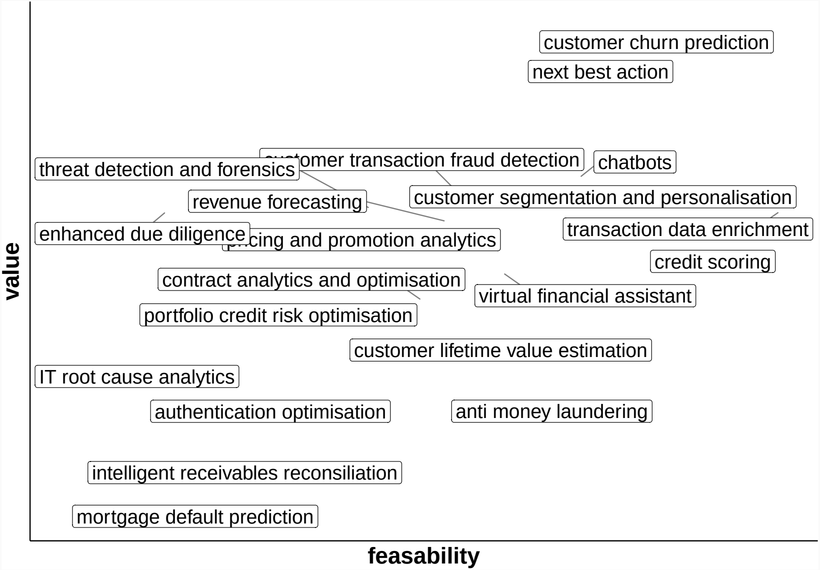
- **reduce operational costs**: process automation, decision intelligence, process screening
- **customer experience**: robo advisors, chatbots (e.g. BoA "Erica", HSBC "Amy", SEB "Aida")

Use Cases for AI in Banking



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  - effect on image as they "show empathy" and help customers in difficult situations

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  - 30% of the total sales attributed to this initiative

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  - more customers in difficult segments

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- Cultural differences (e.g. there is more trust towards AI in Germany than UK) – involve people early – be transparent

Organisational AI maturity: Where are you?

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- Level 2: **AI lab phase** = Activation

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Stay in control

Assure compliance with rules and regulations, enforce ethical standards, avoid the ING scenario (bad press because perceived improper use of data)

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  - How can we re-use the solution and learnings?

Example 1 of AI Governance – RBS

- RBS (Natwest) has a dedicated Data Science team that encompasses
    - the hardware
    - the data ingestion
    - the data structure and governance (lake, big data, structured data, golden source, use monitoring, passporting, etc.)
    - the analytics (dynamic dashboards, ad hoc decision support, mcda) with dedicated client centric teams for
        - Private Bank
        - Retail Bank
        - The rest

Example 2 of AI Governance – BNP Paribas

Dedicated "AI trust and risk mangement team", closely collaborating with

- Model Risk Management
- conduct and compliance risk
- operational process risk and resilience
- data protection, cybersecurity, and privacy risk
- information security risk
- cloud and technology risk
- third party technology risk

The Future Impact of AI

The impact of AI will be proportional to how much we can re-invent and rethink the business itself

Conclusions

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