





Fine-tune a Large Language Model for food and feed safety

Lessons learned from the AI4NAMs project (OC/EFSA/SCER/2021/08) "Exploring the use of Artificial Intelligence (AI) for extracting and integrating data obtained through New Approach Methodologies (NAMs) for chemical risk assessment"

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Carsten Kneuer

Toxicology of Active Substances
Department for Pesticide Safety (BfR)

Carla Mereu

Head of d-fine Italy

The project Al4NAMS, divided into three phases, has been completed in July 2023

- search and extraction
- harmonisation and pre-validation
- Integration in AOP-like networks



List of suitable Al-tools for each of the three steps



Results (partly) published in 01

B Prototyping

- Development of case studies in the context of chemical risk assessment
- Prototypical application of most promising AI tools to case studies



- Chemical- and endpoint-centred case studies
- Detailed study protocols for a selection of case studies
- Implementation of selected case studies incl. documentation

C Outlook

- Retrospective on the lessons-learnt on the AI tools for their prototypical application to NAM data
- Recommendations for the application of AI methods for the usage of NAMs data in risk assessment



- Repository and documentation of the *applied* AI-tools
- Updated review of the *available* Al-tools for NAMs
- Comparison and assessment of the *applied* techniques

Project consortium

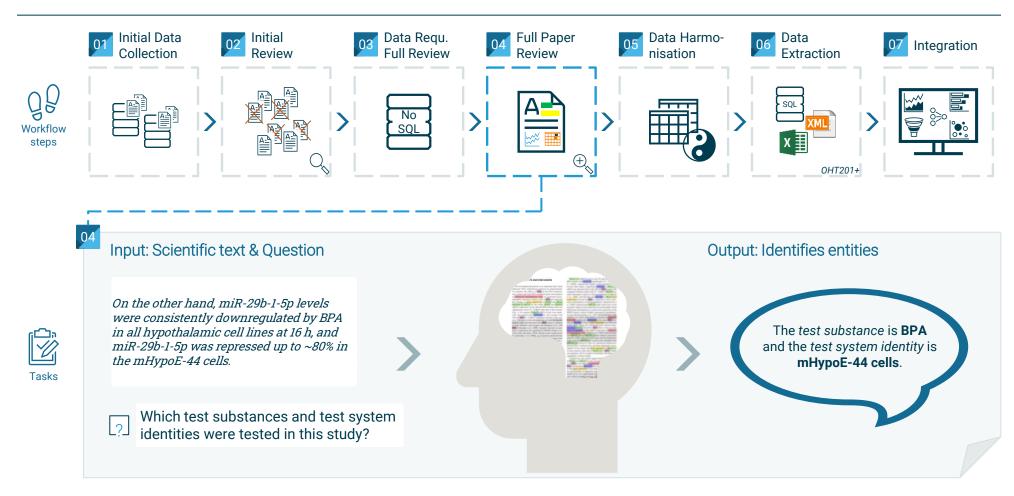






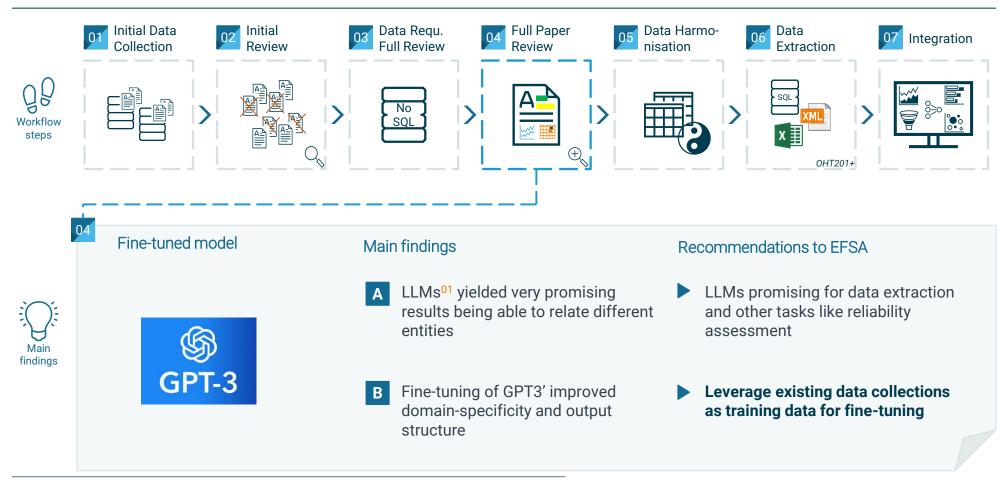
Goal of this project was to systematically explore the potential of applying AI-methods to NAM-data collection and integration, supporting better chemical risk assessment while reducing animal testing.

Selected Al⁰¹ tools and methods have been applied on NAM⁰²-data in a seven-step workflow, a crucial step was concerned with data extraction



Today we will focus on the result of the extraction exercise, focussing on the most promising approach resulted from the implementation of different combinations of tools within 6 case studies, i.e. the fine-tuning of LLMS⁰³.

Our project results highlighted the superiority of LLMs



01 Large Language Models

The accuracy and reliability of the models' results is not yet good enough to enable automation But approaches can be found for the tools to best support the scientists' work.

Exemplary publication: Hoffmann et al. (2017)⁰¹

Focus: Results section



Test substance	Test system identity	Process	Object	Action
BPA	OVCAR-3 cells	cell proliferation		increase
BPA	KGN cells	cell proliferation		increase
BPA	OVCAR-3 cells	gene expression	GPR30	unaffected
BPA	KGN cells	gene expression	GPR30	unaffected
BPA,G15	OVCAR-3 cells	cell proliferation		reduced
BPA,G15	KGN cells	cell proliferation		reduced

01 http://dx.doi.org/10.1016/j.tiv.2017.08.009

Information retrieval Asking for 2 entities



Question

Which test substances and test system identities were tested in this study?

Answer - Experts

Test substance BPA Test system identity embryonic hypothalamic cells

Plain model

Substance | Test System BPA | Embryonic hypothalamic cells



Fine-tuned model

Test substance BPA Test system identity mHypoEN44 cells⁰²



Information retrieval – example Asking for 4 entities (1/2)



Question

What are the test substances, biological processes, biological objects and corresponding actions identified in this study?

Answer - Experts

Test substance Process		Action
gene expression	Dnmt1	reduced
gene expression	Dnmt3a	decrease
gene expression	Dnmt3b	increased
gene expression	Mecp2_e1	increase
gene expression	Mecp2_e2	increase
	gene expression gene expression gene expression gene expression	gene expression gene expression gene expression gene expression gene expression Dnmt3a Dnmt3b gene expression Mecp2_e1

Plain model

Test substance: BPA

Biological process: DNA methylation Biological object: Dnmts and Mecp2

Action: BPA affects the gene expression of Dnmts and Mecp2



- * Model output partially correct, but
 - Missing entries
 - No linkage between entities

Information retrieval – example Asking for 4 entities (2/2)



Question

What are the test substances, biological processes, biological objects and corresponding actions identified in this study?

Answer - Experts

Test subst	ance Process	Object	Action
BPA	gene expression	Dnmt1	reduced
BPA	gene expression	Dnmt3a	decrease
BPA	gene expression	Dnmt3b	increased
BPA	gene expression	Mecp2_e1	increase
BPA	gene expression	Mecp2_e2	increase

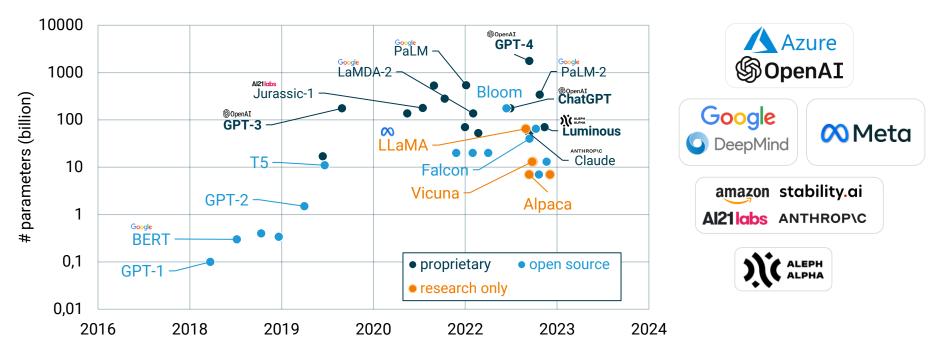
Fine-tuned model

Test substance Process		Object	Action
BPA	DNA methylation	nan	alteration
BPA	gene expression	Dnmt1	reduced
BPA	gene expression	Dnmt3a	increased
BPA	gene expression	Dnmt3b	increased
BPA	gene expression	Меср2	increased
BPA	gene expression	Mecp2_e1	increase
BPA	gene expression	Mecp2_e2	increase
BPA	gene expression	Mecp2	decrease
BPA	gene expression	Mecp2_e1	decrease
BPA	gene expression	Mecp2_e2	decrease

The landscape of language models is very large and rapidly evolving

Selection of (large) language models

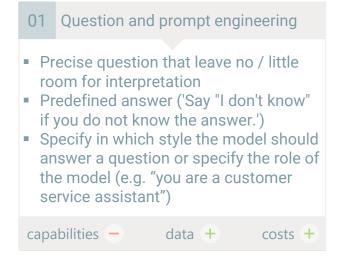
Some key players

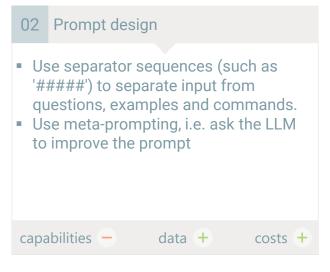


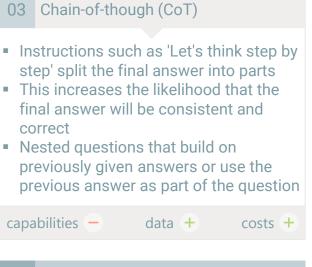
- Dynamic field with many commercial and open-source initiatives
- Models have different scope, e.g. foundation models, instruction-tuned models and task-specific fine-tuned models
- Model size and training strongly impact performance
- Models differ significantly in terms of quality
- GPT-4 achieves the best overall quality at the moment

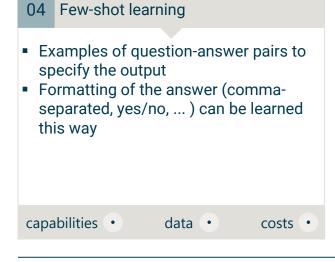
The optimal model selection depends on individual requirements such as task complexity, cost, speed, reliability, data privacy & security, customizability, ...

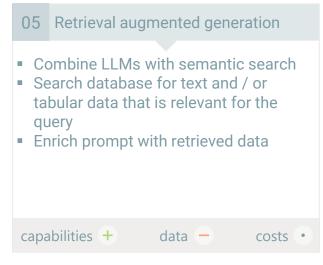
For an optimal domain-specific model, few-shot learning and fine-tuning can be used for optimizing the performance of LLMs













Fine-tuning requires an investment in input and effort but can yield tangible advantages in selected cases



Definition – Fine-tuning⁰¹

Fine-tuning means supervised fine-tuning⁰², i.e. the process of retraining pre-trained models on specific datasets, typically to improve model performance on specific tasks or introduce information that wasn't well represented when the base model was originally trained.



Advantages of fine-tuning

- Higher quality results than what you can get just from prompt engineering.
- The ability to train on more examples than can fit into a model's max request context limit.
- Lower-latency requests, particularly when using smaller models.

Exemplary training input

BPA

However, as BPA concentra Text: agent has the potential to a In our results, the gene key players that provide sta more sensitive than the epigenetic gene regulation. Correct answer: Correct answer: Test substance Proce BPA

gene BPA

Test substance

Our results suggest that BPA has the potential to directly alter the gene expression levels of Dnmts in embryonic hypothalamic cells; however, these effects are not seen at the doses at which dendritic and synaptic development are affected.

Correct answer:

Test substance

Test system identity embryonic hypothalamic cells



Exemplary fine-tuning workflow⁰¹ (Azure / GPT)

- Prepare your training and validation data.
- Train your custom model.
 - Select a base model.
 - Choose your training data.
 - Optionally, choose your validation data.
 - Optionally, configure advanced options for your fine-tuning job.
 - Review your choices and train your new custom model.
- Check the status of your custom fine-tuned model.
- Deploy your custom model for use.
- Use your custom model.
- Optionally, analyze your custom model for performance and fit.

01 cf. https://learn.microsoft.com/en-us/azure/ai-services/openai/concepts/fine-tuning-considerations

02 To be distinguished from continuous pre-training or Reinforcement Learning through Human Feedback (RLHF)

Contacts



Dr Carsten KneuerHead of Unit, Toxicology of Active
Substances and Their Metabolites, BfR
Tel +49 30 1841226300
Carsten.Kneuer@bfr.bund.de



Dr Carla Mereu Head of d-fine Italy Tel +39 348 1988969 Mobile +39 348 1988 969 Carla.Mereu@d-fine.com