

Medical AI - How Machine Learning Can Help Your Publishing Career

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1 Poll



Figure 1: Entry survey for participants

Poll responses at: <https://tinyurl.com/wrmc-poll-done>

2 Title

The image on the right was created by leonardo.ai, an AI for graphic design and image generation using the prompt: "Inspirational image for a lecture on medical artificial intelligence to medical residents," using the DreamShaper v7 model (created on 02/08/23).

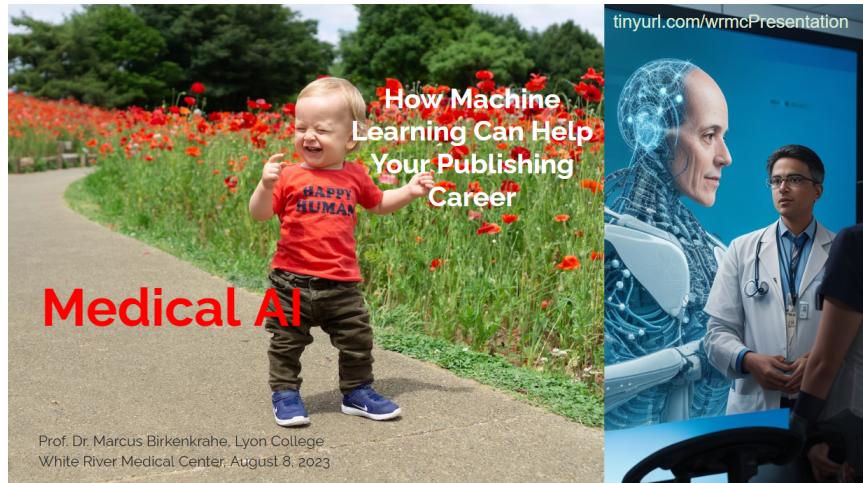


Figure 2: Images: unsplash.com and leonardo.ai

3 Who am I?

I would not normally spend so much time talking about my own person - except perhaps at the start of a semester-long class. I feel that it is indicated for three reasons:

1. I am an expert of some, but not on all of AI which is a vast field
2. I am not a physician but a physicist
3. I'd like for this talk to be the beginning of a fruitful collaboration between Lyon College and WRMC.

3.1 Youth

I am very excited to be here and speak to my very first group of medical residents ever on AI. I'm not a physician but a physicist. My closest personal connection to your profession is through my dad who was an anaesthesiologist, who worked a lot and often took me to the hospital, which I remember as a place of play. I remember doctors and nurses fondly as people trying to keep me out of harm's way, which wasn't easy because I was a very active, curious child.



Figure 3: Boy in Emerson Respirator, Nat'l Mus of Health and Medicine



Figure 4: DESY, Hamburg, Germany, 1994.

3.2 Research

Advised by my father, the doctor, not to become a doctor, I became a theoretical particle physicist instead, which ultimately lead to computing and data science. Thirty years ago, as a graduate student, I dabbled in and published on neural networks, which form the technical basis of most of what I'll talk about today, Large Language Models like ChatGPT.

3.3 Industry



Figure 5: London with Shell Centre and the London Eye, UK

Because I was in the right place at the right time (particle physics research at CERN), I was able to contribute to the original development of the WWW (often mistakenly called "The Internet") in the early 1990s. This opened new opportunities for work outside of academia and I spent a few years in industry - mostly working in knowledge management, which is another important application area of AI.

3.4 Teaching

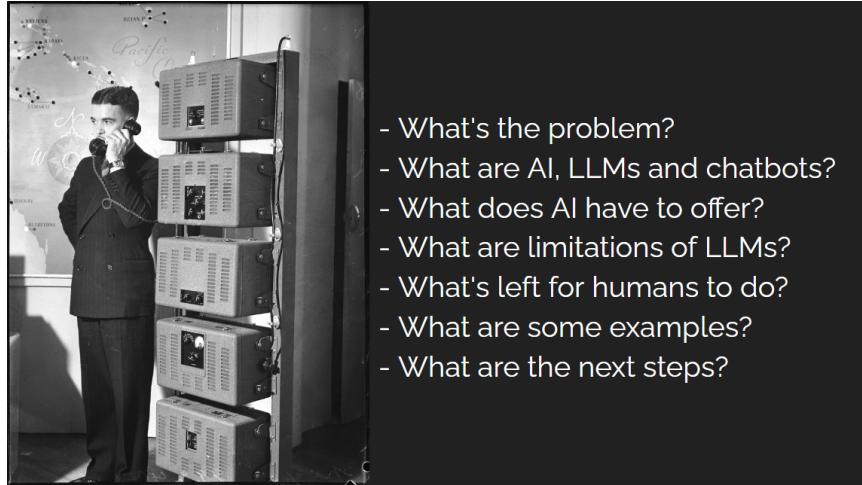
These days, I teach computer and data science, including machine learning, data visualization, game programming and robotics to undergraduates and



Figure 6: UBMS class "Game and Robotics programming with Snap! and Python"

upward bound math and science high school kids (photo). In terms of raw output, I've published 60 peer-reviewed articles so far. My current (new) research focus is AI-assisted literate programming for data science.

4 What's on the agenda



- What's the problem?
- What are AI, LLMs and chatbots?
- What does AI have to offer?
- What are limitations of LLMs?
- What's left for humans to do?
- What are some examples?
- What are the next steps?

Figure 7: Slide: questions covered in this presentation

Here are some of the topics I'd like to cover in the next hour. I'll begin by clarifying the problem we're trying to address with AI.

The field of AI is young in years but because it is focused on optimization in the most general sense, we need to narrow it down severely. Hence we'll begin by talking about the problem of publishing that was promised in the title, and we will try not to stray too far from it so that we can achieve anything in the short time.

Then we'll look at the part of AI in the eye of the hype hurricane - Large Language Models as part of a subfield of AI called Deep Learning. To appreciate what these models can and cannot do, we need to understand at least in principle how they work.

In preparation for this talk, I have conducted many little experiments with several conversational AI applications or chatbots as they used to be called. All experiments were focused on scientific paper production.

This field is in extreme flux right now - new tools are emerging all the time, and I want to summarize the most likely roads of future development

that may help you in your publishing career.

5 Part I: What's the problem?

Here are four aspects of research, not just research writing, that make scientific publishing challenging:

- Research requires skills
- Research takes time
- Research data are critical
- Research writing is standardized

5.1 Research requires skills

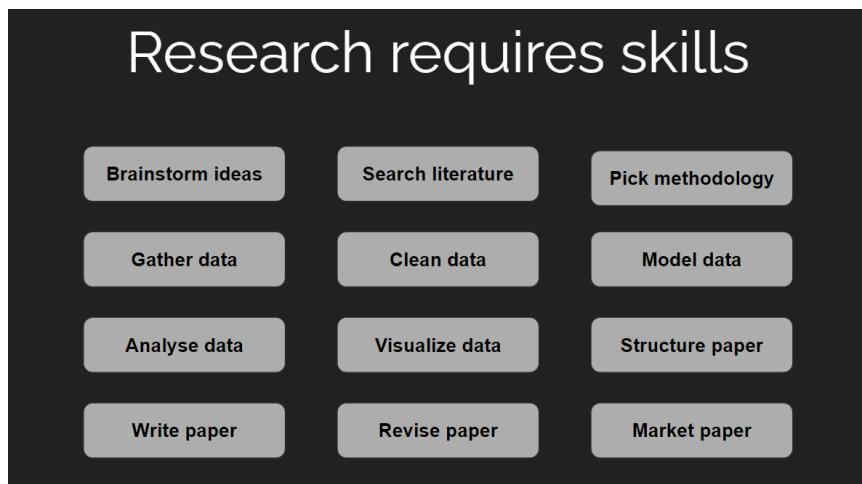


Figure 8: Slide: Research skills

This is only a subset of (more or less loosely ordered) specific activities under the general umbrella of "research" in any field. The abstract concepts are deceptive: in reality, every step is highly customized and customizable depending on the scientific discipline.

Example: a typical particle physics experiment of today generates ca. 100 TB of data for analysis per second. By comparison, an X-ray represents information of the order of 1 MB - physics works with 100 million times as much information hitting the computers per second.

The data volume ("Big Data" - high volume, high velocity and low variety in physics; low volume, low velocity, high variety in medicine) influences all other skill areas. Example: it is no longer possible to evaluate particle physics experimental results manually. Most of the pre-analysis efforts go into cleaning the data for processing and visualization.

Specifically for publication: a typical experimental particle physics paper has hundreds of authors. A (by now) standard way to prevent fraud is to make all data available: for physics data, this requires dedicated big data infrastructures designed specifically for the experiment.

Another difference is methodological: most of the published papers that I've seen come out of WRMIC were "case reports" to draw qualitative conclusions for treatment based on a small sample of quantitative data. This is a typical methodology in applied sciences that are focused on humans where experiments cannot be repeated easily (if ever) and where special ethical considerations rule.

There's a trend here: a growing importance of data, and a greater need for technological augmentation or automation. One price to pay (besides money) for methodological and technological innovation is having to unlearn old skills and pick up new skills at an unprecedented rate.

For a recent (3 August 2023) literature review on "Scientific discovery in the age of artificial intelligence", see: Wang, H., Fu, T., Du, Y. et al. Scientific discovery in the age of artificial intelligence. *Nature* 620, 47–60 (2023). <https://doi.org/10.1038/s41586-023-06221-2>

5.2 Research takes time

You know this of course: having an individual skill is not enough, you also have to have the time, stamina and experience required to iterate these steps perhaps not ad infinitum but (for some of these) many times until you have even reached the "writing" phase.

The ability to iterate efficiently is developed, alas, only over time itself and often eludes young researchers, or researchers who work alone without the support of more experienced researchers.

High number of iterations are required for: searching the literature, modeling, analysing and visualizing the data. AI augmentation here has the greatest impact on saving time.

Things aren't quite as clear for the last three steps - these may also have to be iterated but not nearly as many times as the research process steps themselves:



Figure 9: Slide: Many research activities are highly iterative

1. Writing the paper is inherently highly time-consuming but can be much more so if you don't write in your native language, or if you're not in full possession of technical language (e.g. because of lack of experience or when you've just entered a new field).
2. Revising the paper takes time because it often involves (ample) correspondence with the publisher and/or reviewers. The less experienced a researcher is the more time he or she will have to spend on it.
3. Marketing the paper is no longer just the responsibility of the publisher: I checked and found that many residents maintain accounts at researchgate.net and have ORCID numbers. To stand out, they are likely active on other social networks, too, like Twitter or LinkedIn. Some may even have their own blogs. A fair amount of extra writing in a very specific style is required to do social network communication well.

To get started on AI augmentation examples, see this conversation on one of my own sentences above and the use of a word. This could be a typical exchange for a non-native speaker who tends to overuse or misuse words. In a non-AI scenario, I'd have to look at a translation engine like linguee.com or deepl.com (that also use AI).



Figure 10: Slide: illustrating data science as a critical research skill

5.3 Research data are critical

I've already commented on the importance of having data-related skills, which are related to IT rather than one's own medical research.

Data science is a very young, highly interdisciplinary field that gets all its importance from the need to turn raw data into actionable insights using programming and statistics knowledge. "Story" is a synonym for these insights, and the terms "data storytelling" and "data literacy" both relate to it.

I'm highlighting this sub-skillset because I am most acquainted with it but also because "data science" includes "machine learning", the part of AI that is responsible for conversational apps like ChatGPT.

As a medical researcher, it will in the future be critical to have a working knowledge of at least one of these areas: data manipulation, coding, statistics or storytelling. A fair knowledge of statistics seems to be required according to my brief look at medical papers. The need for coding may be alleviated through low-code or no-code platforms, or AI assistants, but it will never completely disappear if you work with computers (a "no-code" platform simply requires different 'coding' skills but it still produces code). Data manipulation is essentially an engineering task and highly technical. By contrast, storytelling can be considered more creative - see however this paper for parallels between storytelling and IMRaD: M. Birkenkrahe, "Using storytelling methods to improve emotion, motivation and attitude of students

writing scientific papers and theses," 2014 IEEE 13th International Conference on Cognitive Informatics and Cognitive Computing, London, UK, 2014, pp. 140-145, doi: 10.1109/ICCI-CC.2014.6921453.

5.4 Research writing is standardized



Figure 11: Slide: IMRaD structure of scientific papers

The standardization of scientific writing is the only good news in this pile of problems: all publications follow the IMRaD structure, where:

1. the "Introduction" says **why** the author wanted to do the research (including a literature review for validation),
2. the "Method" says **how** the author wanted to do it and how it was done in the end (not necessarily the same method),
3. the "Results" say **what** the author found out through this research (including, quite possibly, nothing much),
4. the "Discussion" says **why** anybody should pay attention, and what the results (or lack thereof) mean in the context of other research on the same or a related topic, including limitations of the research.

Standardization is an opportunity for automation as long as it is reliable. In fact, as we will see, the success of AI in using scientific documents to comment upon and help support new scientific research largely depends on

the standard structure of the documents that the LLMs have gobbled up, and open the path to better, more customized AI assistants - for example only for medical research.

5.5 Summary I

Summary



- Scientific publishing requires a wide range of **skills**, ample **time**, and data **literacy**.
- Scientific writing is **standardized** through the **IMRaD** structure, with opportunities for **automation**.
- **Data science** skills are becoming critical (data + code + stats = story)

Figure 12: Slide: summary for part I (what's the problem?)

6 Part II: What's the solution?

Glad you asked. In this second part of my talk, we'll delve into understanding what AI is and how it can support medical research publications. This foundational knowledge will help you appreciate the examples and conclusions I'll present later on.

Please remember, I didn't promise an introduction to "Medical AI" in its broadest sense. That would necessitate a completely different talk and might not be as relevant to your diverse specializations.

Delving into AI, particularly in the medical field, is complex. To illustrate, consider a recent study from July 2023: economists at MIT conducted an experiment involving 180 tele-radiologists both within and outside the US. With AI assistance, they encountered several challenges, even though the AI's performance was on par with human expertise. One author on Twitter: "We gave 180 radiologists an expert-level AI for diagnosis. But instead of improving, their performance didn't budge. Why? Radiologists

implicitly discount AI predictions, favoring their own judgement - a bias we call 'automation neglect'." A clinician on Twitter responded critically, suggesting, "AI proponents need to engage clinicians without undermining our intelligence or alienating us." I take that feedback seriously!

David S Chang 
@dschan02

Many clinicians like myself have a high burden of mistrust toward "AI" because we've spent the past 15 years hearing pitches from software vendors selling "super intelligent AI" that turns out to be a crappy database or a misleading data visualization. (or a parlor trick like IBM Watson Oncology)

If medical AI is ever to succeed in treating real-world patients, the AI folks will need to figure out how to talk to clinicians in a way that doesn't insult our intelligence or scare us off.

10:53 PM · Jul 31, 2023 · 1,010 Views

Figure 13: David S Chang (@@dschan02) on Twitter, July 31, 2023.

For further insight, you can check out my conversation with ChatGPT. I sought a summary, participant data, references, a list of limitations, and details about the methodology and experimental design used.

Reference: Agarwal N, Moehring A, Rajpurkar P, Salz T. Combining Human Expertise with Artificial Intelligence: Experimental Evidence from Radiology. MIT Department of Economics; National Bureau of Economic Research. July 2023. (Link to the white paper.)

6.1 Artificial Intelligence Applications

Artificial Intelligence (AI) is a fairly large field of science - it's large even though it's young as an area of systematic inquiry (70+ years) because of the many areas of human activity that it has touched, including:

1. Healthcare:
 - Medical diagnosis
 - Predictive analytics for patient care
 - Drug discovery and design
 - Medical image interpretation



Figure 14: AI image auto-generated by leonardo.ai with text prompt

2. Finance:
 - Algorithmic trading
 - Fraud detection
 - Credit scoring
 - Personalized banking services
3. E-commerce:
 - Recommendation systems
 - Customer service chatbots
 - Price optimization
4. Transportation:
 - Autonomous vehicles
 - Route optimization for delivery trucks
 - Predictive maintenance for vehicles
5. Entertainment:
 - Content recommendation (e.g., Netflix or Spotify)
 - Video game AI
 - Virtual reality simulations
6. Marketing:
 - Targeted advertisements
 - Customer segmentation
 - Predictive sales analytics
7. Manufacturing:
 - Predictive maintenance of machinery
 - Quality assurance using visual recognition
 - Robotics for automation
8. Agriculture:
 - Crop and soil monitoring
 - Predictive analytics for crop yields
 - Automated irrigation systems
9. Education:
 - Personalized learning platforms
 - AI tutors
 - Learning analytics and prediction

10. Energy:

- Smart grids for electricity distribution
- Predictive maintenance for energy infrastructure
- Energy consumption optimization

11. Security:

- Facial recognition for surveillance
- Anomaly detection in cybersecurity
- Predictive policing

12. Language and Communication:

- Machine translation (e.g., Google Translate)
- Speech recognition (e.g., Siri, Alexa)
- Text-to-speech synthesis

13. Research:

- Literature review and meta-analysis
- Data mining and pattern recognition
- Simulations and modeling

14. Smart Cities:

- Traffic management and optimization
- Waste management
- Energy-efficient buildings

15. Space Exploration:

- Rover autonomy (e.g., Mars rovers)
- Satellite image analysis
- Predictive modeling for space missions

Most AI is embedded in systems quite literally "out of sight".

The image was created by leonardo.ai, an AI for graphic design and image generation using the text prompt: "Inspirational image for a lecture on medical artificial intelligence to medical residents," and this image prompt, a modern painting of the battle at Gettysburg by Don Troiani, using the DreamShaper v7 model (created on 02/08/23).

6.2 Large Language Models (LLMs)

We'll start exploring this diagram from the bottom.

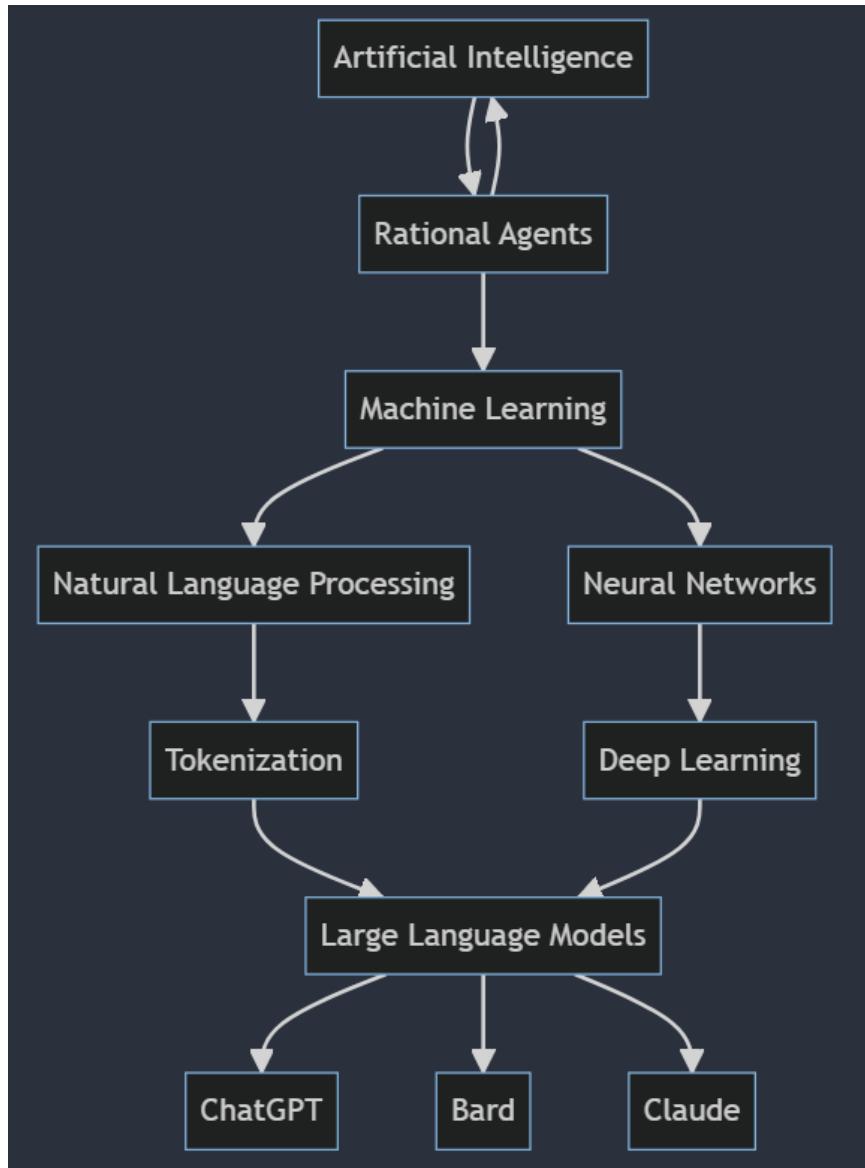


Figure 15: AI subfields (Mermaid diagram by Claude 2, my prompt)

- **What is ChatGPT?** ChatGPT is a conversational, web-based interface for a GPT or Generative Pre-trained Transformer model created and owned by OpenAI (which despite its name isn't all that open), and made available freely in November 2022. There are also GPT APIs (Application Programming Interface) that can be used in code - for anyone who wishes to use the model for his or her own purposes. For example, as soon as the ChatGPT API was opened in early 2023, my students and I were using ChatGPT directly in our own applications - and this is the real driver behind the current AI hype.
- **Large Language Models (LLMs)** is the class of models to which GPT models like ChatGPT and its siblings, Bard by Google, Bing Chat by Microsoft and Claude by anthropic belong. LLMs are the result of Natural Language Processing (NLP) using an Artificial Neural Network (ANN) architecture.
- LLMs are trained on existing text to use probability distributions over words and word sequences to generate output in the form of new words. This means that the model computes the likelihood of the next word it prints based on the words and sentences it already knows.
- This "layman's" explanation given by ChatGPT (GPT-4 August 3 version) is actually pretty good:

"A Large Language Model, like the one you're talking to, is a kind of computer program designed to understand and generate human language. Think of it as a super-smart digital parrot. It's been "trained" by reading tons of text from books, websites, and other sources. When you ask it a question or give it a prompt, it doesn't "think" or "know" in the way humans do. Instead, it predicts the best response based on patterns it learned from all that text. It's like if you blended all the books in a library together and then tried to have a conversation with that blend. This program can help answer questions, write stories, and more, all by mimicking human language."

- Deep learning refers to the class of Neural Networks necessary to process very large amounts of text to create the LLMs, and Tokenization is the way in which NLP uses the ANNs to manage text.

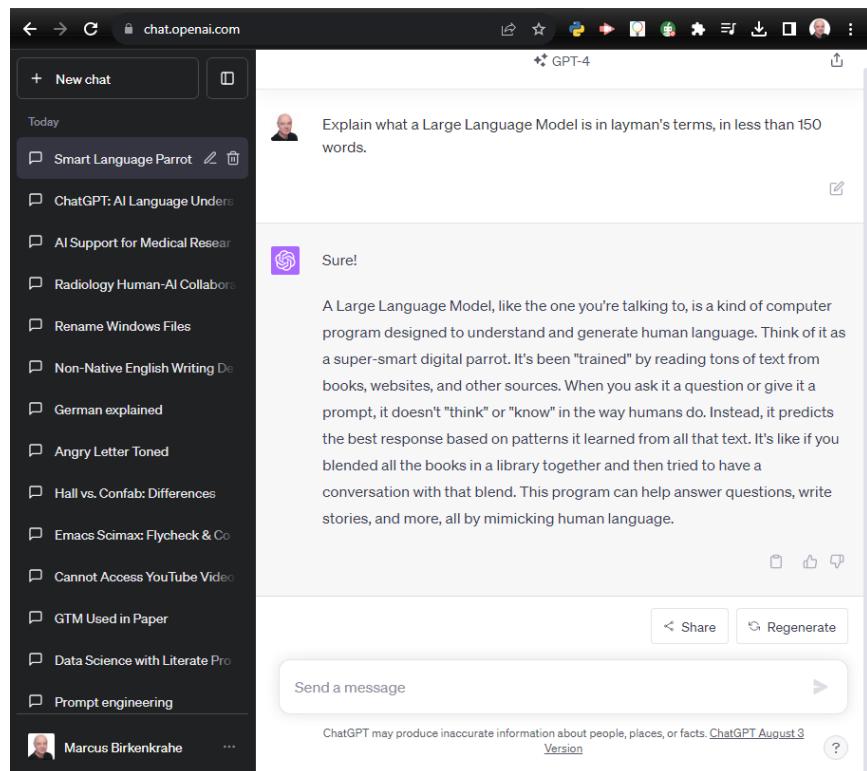


Figure 16: ChatGPT's Layman's explanation of a Large Language Model

- "Tokenization" refers to turning human-readable words into sequences of number IDs where a token can correspond to more than one word - on average, in English, 75 words can be broken down to 100 tokens.
- All conversational AI is limited with regard to the number of tokens that it can process at any one time (for a prompt response). In ChatGPT this can lead to the AI refusing to do the work when the token limit is reached. This token limit does not directly translate into bytes because it depends strongly on the model.

6.3 How do Large Language Models work?

- Neural networks connect a vast amount of input nodes to hidden layers to one output layer. Different purposes require different specific architectures.

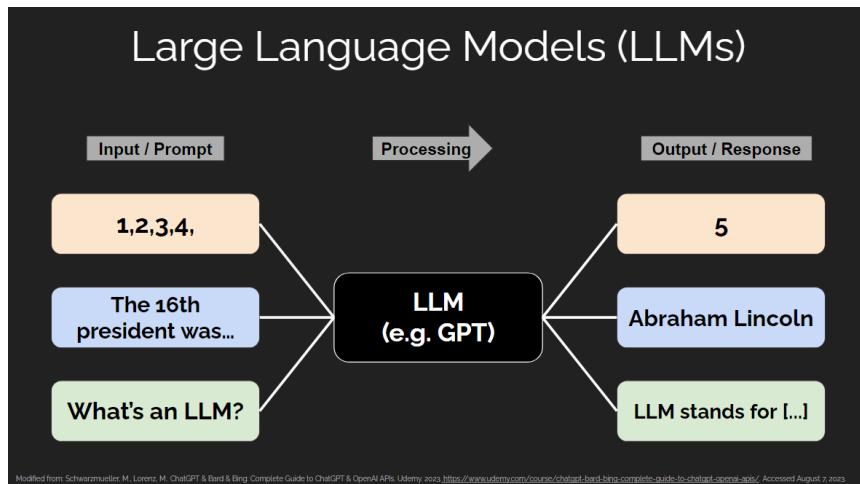


Figure 17: Slide: LLMs are black-box-models specialised on word completion

- Predicting the next word as output based on a given input, or a response based on a prompt as shown here with a few examples, is all that the LLM does - without ever understanding anything (just like a "digital parrot").
- The LLM itself is largely a "black box", even to its creators. After the pre-training on raw data and the fine-tuning, the model itself is

not open to scrutiny and change. Of course, there are several layers between the model and its web application, which are subject to changes - but the model itself, the way in which given input leads to stochastically computed output - cannot be changed until a new model was trained. Which in the case of LLMs, takes weeks and millions of dollars. That is the "version", which you see at the bottom of the ChatGPT interface.

6.4 How are Large Language Models trained?

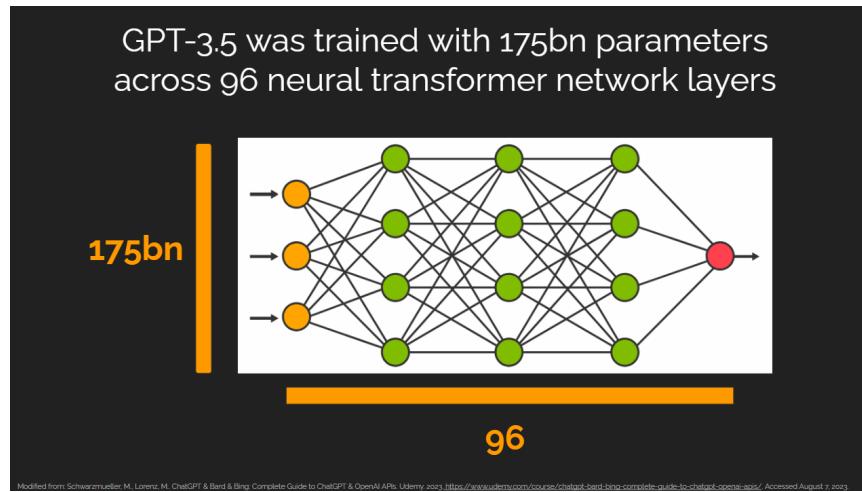


Figure 18: Slide: GPT-3.5's training parameters and network architecture

- GPT-3 by Open AI was pre-trained on several data sets, totalling ca. 570 GB of data. It was trained with 175bn parameters (input nodes) across 96 network layers of a transformer neural net.
- It is estimated that GPT-4 by Open AI is based on eight different models, each trained with 220bn parameters (input nodes) totalling 1.76 trillion parameters.
- You can think of these "parameters" as rules that determine the meaning of a word or a word sequence in the input. For example, to complete a sentence like "Today, the sun is very... ", you have to choose between words like: 'glass', 'drop', 'hot', 'blue' etc. "Training" the network establishes relationships that enable the final model to rapidly, and with

high probability, decide that the likely end of the sentence is "Today, the sun is very HOT."

- Language rules are not only used in LLMs but also in traditional NLP applications like sentiment analysis, when for example a marketing agency wants to create a campaign for a product based on a large number of real tweets: the rules are then used to compute an index for the "polarity" of the tweet with regard to the product.
- What were the LLM training data? Essentially the entire text information publicly available on the Internet. Training also involves semi-manual tuning to remove "toxic" content.

6.5 Summary II

Summary II

AI impacts **multiple sectors**, from healthcare to space exploration, with its applications often being seamlessly integrated into systems.

Large Language Models (LLMs): mimic human language by generating word or sequence responses from patterns in vast text data.

LLMs use artificial **neural networks** to predict responses based on input, often remaining mysterious even to their creators.

OpenAI's GPT-3 and GPT-4 were **trained** on extensive datasets from the internet, with billions of **parameters** guiding responses.

Figure 19: Slide: Summary Part II (AI and LLMs)

- Artificial Intelligence Applications: AI impacts multiple sectors, from healthcare to space exploration, with its applications often being seamlessly integrated into systems.
- Large Language Models (LLMs): LLMs, developed through NLP and ANN architectures, mimic human language by generating responses from patterns in vast text data.

- How do Large Language Models work? LLMs use neural networks to predict responses based on input, often remaining mysterious even to their creators.
- How are Large Language Models trained? GPT-3 and GPT-4 were trained on extensive datasets from the internet, with trillions of parameters guiding their responses.

Images: two images in response to a text prompt ("Summarize a chapter on Artificial Intelligence Applications, Large Language Models, and neural networks.") and an image prompt (Truckload of apples in orchard. Camden County, New Jersey (LOC)), created by the Leonardo Diffusion model at leonardo.ai (Aug 7, 2023).

7 Part III: How can you use it?

7.1 What's different about ChatGPT

I've spent a few months trying stuff out, and also using AI while writing an actual paper of my own: Birkenkrahe, M. Teaching Data Science with Literate Programming Tools. Preprints 2023, 2023071847. doi.org/10.20944/preprints202307.1847.v1.

These slides contain the documentation of a number of my experiments, especially concerning:

- Prompt engineering
- Summarizing text and video (!)
- Proofreading
- Utility tasks (automating routine PC tasks)
- Improving graphs
- Coding in interactive notebooks with ChatGPT
- Researching stuff (and getting frustrated about lies!)
- Citing AI assistance in your work (or not perhaps).

At the outset: how exactly is ChatGPT different from Google Search?
It is different in a number of ways:

1. It is "conversational" in the sense that it remembers the conversation you had with it (for one session).

2. It is "considerate" in the sense that it tries to provide output as close to your prompts as possible (within its means).
3. It is not commercial, i.e. free of advertisements (for now). Don't underestimate how lovely this is - it makes for a clean, focused experience (after all, you don't interrupt intimate conversations or productive meetings with commercials, right?).

It is similar, identical even with regard to two other properties:

1. It is mindless like a telephone book (or, if you don't know what that is anymore, like a printed manual).
2. It is vast and can be all-absorbing so that you lose all your available time and nerves dealing with the machine rather than with your problem (using your own head).
3. It is not available as an act of kindness or to improve the quality of your life or to make the world a better place (though that was part of OpenAIs original goal, as it was for Google, Facebook etc.) but to make money.

7.2 How ChatGPT thinks it can support your publishing

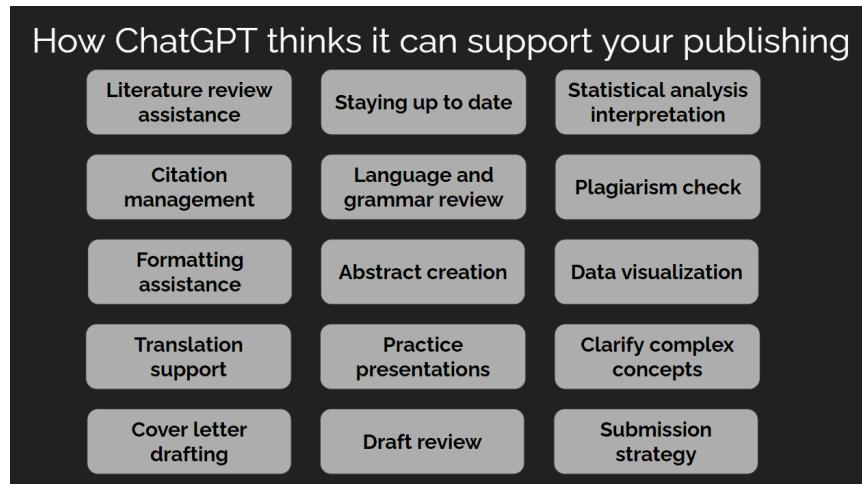


Figure 20: Slide: how ChatGPT thinks it can support your publishing

I asked ChatGPT (August 3 version of GPT-4 default): "The target audience is medical residents. They need support with their scientific publications. Give me a list of ways in which you could support them!"

ChatGPT's response:

Certainly! Here's a list of ways in which a tool like mine could support medical residents with their scientific publications:

1. Literature Review Assistance: I can help identify relevant articles, journals, and studies based on keywords or topics, streamlining the research process.
2. Draft Review: Provide feedback on drafts, ensuring clarity, coherence, and proper structure.
3. Statistical Analysis Interpretation: Help in understanding and interpreting statistical analyses, outcomes, and significance levels.
4. Citation Management: Offer guidance on the proper format for citations and references based on the desired citation style (e.g., APA, MLA, AMA).
5. Plagiarism Check: While I can't replace dedicated plagiarism software, I can help identify and rephrase sentences that might be too close to original sources.
6. Language & Grammar Review: Ensure the manuscript uses proper grammar, spelling, and scientific terminology.
7. Formatting Assistance: Provide guidance on formatting manuscripts according to specific journal guidelines.
8. Data Visualization: Offer insights on how to best visualize data, whether it's through graphs, charts, or tables.
9. Abstract Creation: Aid in condensing findings into a succinct and coherent abstract.
10. Translation Support: Provide translations for abstracts or entire articles to reach broader audiences.
11. Clarify Complex Concepts: If there's a challenging concept, I can provide explanations or analogies to ensure accurate understanding.
12. Practice Presentations: For residents who need to orally present findings, I can provide Q&A sessions to prepare.

13. Cover Letter Drafting: Assist in drafting cover letters for manuscript submissions to journals.
14. Stay Updated: Provide updates or summaries on recent publications in the resident's field of study, ensuring they are aware of the latest research.
15. Submission Strategy: Offer insights on which journals might be most appropriate for their research based on scope, impact factor, and audience.

By leveraging these supports, medical residents can navigate the often challenging process of scientific publication more confidently and effectively.

7.3 Where I think ChatGPT shines, and where it stinks

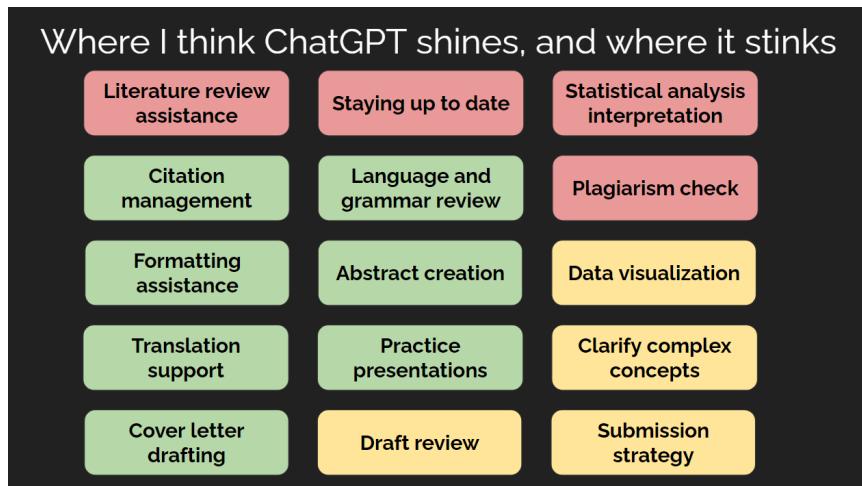


Figure 21: Slide: where ChatGPT shines and where it stinks

Now, I have spent a couple of months testing most of these. My summary verdict is: this particular list is not confabulated. ChatGPT (and, to a different degree, with different emphases, also its LLM siblings) is capable of assisting you with all these activities.

Here, I only want to comment on a few of the "yellow" (not so great!) and "red" (beware!) ones that are most important to my work:

1. **Literature review assistance** and **Staying up to date** is a possibility if you have web search support, and I have unearthed articles

that I didn't find on my own - but the burden of confabulation is too heavy: especially in the free version (without extra support by scholarly plugins), the model makes up references even when told explicitly not do to it. This gets frustrating fast! Nobody likes to be lied to!

2. **Data visualization and Statistical analysis interpretation** is a creative activity whenever it is really required - but the model is quite literally a "regression to the mean" of all available visualizations and interpretations. This is great when you want to improve a graph (see example later on) or if you need a refresher on how to customize a stacked barplot in Python or R, but if you're up against the unknown, not so much.
3. **Draft review and Submission strategy:** These aren't creative but they're also not completely cookie-cutter. When I used the bot to review a draft, I never learnt anything new that was really interesting or eye-opening (I usually knew what the problem was and that it wasn't easy to fix). And submission strategy has a standard part (which is covered by reading the instructions), and a human part, which is about networking and correspondence. This last part involves a lot of subtle decisions. The AI can help you to write bland, correct letters when needed but it cannot really help you deal with a hostile reviewer.
4. **Clarify complex concepts:** the AI does that but on the level of an encyclopedia. If you're actually an expert (and you should be, to an extent, before writing a paper on your very own research), then Wikipedia cannot help you.
5. **Plagiarism check:** sounds like an easy automation task but because fraud in science is rampant, authors do not need more tools to obscure the true origin of their ideas or their writing. Rephrasing should be done most consciously and deliberately, and not be left to AI.

On the remaining pages, let's look at some examples, including a few not mentioned by ChatGPT (but done well nevertheless)!

For the original documentation that I created as I went along, see here in GitHub. It contains a lot more stops and starts than this presentation, and (in the section "Analyzing scientific publications"), examples for several publications from WRMC residents.

Some of the examples are also not with ChatGPT but instead the (still free to use) Claude 2 model by anthropic. In my classes, I mostly use GitHub Copilot or ChatGPT's Code Interpreter for coding assistance. For (informal)

comparisons, I have used Google's Bard, Microsoft's Bing Chat and Meta's LLaMa via perplexity.ai. ChatGPT, Bing Chat and LLaMa are also available as Android apps.

I also spent too much time playing around with AI image creation - here is a separate presentation documenting my experiments with leonardo.ai.

7.4 Prompt design / engineering

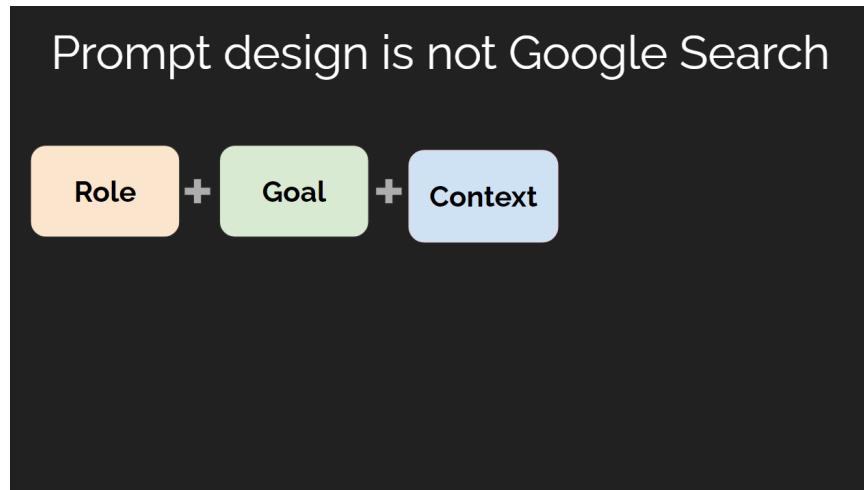


Figure 22: Slide: Prompt design is not Google search

7.5 Summarizing text and video transcripts

- Text (GPT-4 + AI PDF plugin): Summarizing and inquiring about a technical paper on literate programming (full conversation): Mary Beth Kery, Marissa Radensky, Mahima Arya, Bonnie E. John, and Brad A. Myers. 2018. The Story in the Notebook: Exploratory Data Science using a Literate Programming Tool. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18). Association for Computing Machinery, New York, NY, USA, Paper 174, 1–11. <https://doi.org/10.1145/3173574.3173748>
 1. Which research methodology was used in this paper?
 2. Was any other method mentioned?
 3. Did the authors identify any limitations of their research?

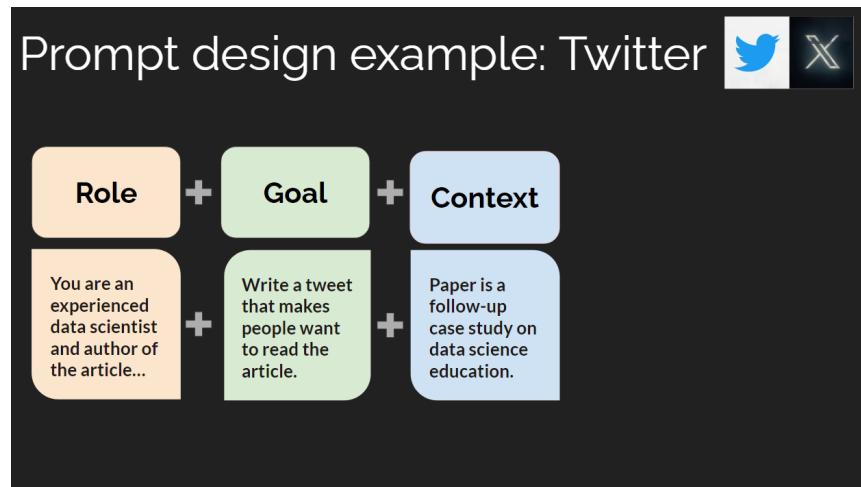


Figure 23: Slide: Prompt design example: Twitter (1)

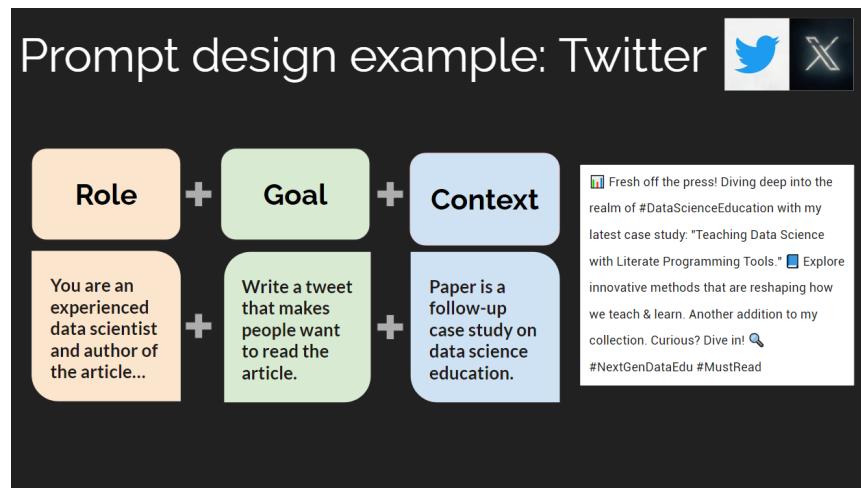


Figure 24: Slide: Prompt design example: Twitter (2)

Prompts are better with target audience

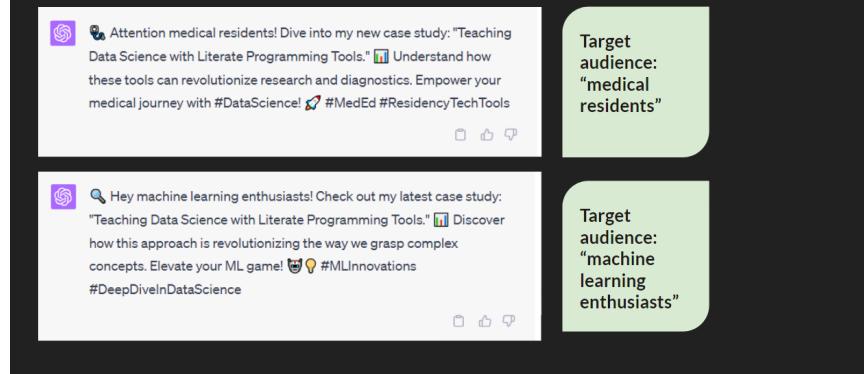


Figure 25: Slide: Prompt are better with target audience

Output control improves your workflow

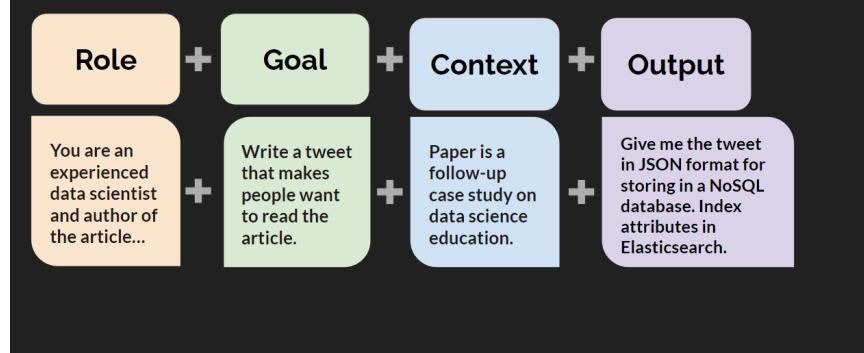


Figure 26: Slide: Response/output control improves your workflow

Tweet in JSON format with ElasticSearch index attributes

```
json Copy code
{
  "_id": "unique_tweet_id",
  "title": "Teaching Data Science with Literate Programming Tools",
  "message": "Hey machine learning enthusiasts! Check out my latest case study on MLInnovations. #DeepDiveInDataScience",
  "hashtags": ["MLInnovations", "DeepDiveInDataScience"],
  "author": "username_here",
  "timestamp": "2023-08-07T14:05:00Z",
  "retweets": 123,
  "likes": 456
}
```

Figure 27: Slide: Tweet response/output as JSON / ElasticSearch

Summarize text and video transcripts



- Which research methodology was used?
- Did the authors identify any research limitations?
- Please summarize the most important conclusions.
- Did the authors miss anything?
- Give me a short summary of the paper.
- Summarize again and use your earlier findings.
- Translate your summary to French. Show a paragraph by paragraph translation.

Figure 28: Slide: summarize text and video transcripts

- 4. Please summarize the most important conclusions.
- 5. Did the authors miss anything?
- 6. Give me a short summary of the paper with the most important points.
- 7. Please summarize again and use your earlier findings for the "methodology".
- 8. Translate your summary to French. Show a paragraph by paragraph translation.
- Video (GPT-4 + VoxScript plugin: Summarize and inquire about a technical video on YouTube (full conversation): Kitchin J. Literate programming in org-mode and scimax. YouTube. Published February 27, 2023. Accessed [Today's Date]. <https://www.youtube.com/watch?v=v3CeZ9TaAWo>.
 - 1. Please summarize this video for me.
 - 2. Is this video useful as an introduction to literate programming with Emacs and Org-mode?
 - 3. How can I find out more about literate programming?
 - 4. How can I find out more about Emacs and Org-mode?
 - 5. What is the difference between Scimax and Emacs?
 - 6. Give me an AMA-formatted citation for this video, please.

7.6 Defuse and translate an angry German letter

Task: Angry letter toned (full conversation)

1. Tone very angry German letter down.
2. Translate the defused letter to English.
3. Show me specifically what you changed.
4. Add a warning to make it sound more serious.

7.7 Proofread texts written by non-native author

- Task: Improve a text (Full conversation.).
- 1. Make up a text that might have been written by a non-native English speaker.

Defuse and translate an angry letter



- Tone an angry German letter down.
- Translate the letter to English.
- Show me what you changed.
- Add a warning to make it sound more serious.

*How would you improve
this sequence of prompts?*

Figure 29: Slide: defuse and translate an angry German letter

Proofread texts written by non-native author



- Make up a text that might have been written by a non-native English speaker.
- Fix the text.
- Tell me what you did exactly.

*How would you improve
this sequence of prompts?*

Figure 30: Slide: Proofread texts written by non-native author

2. Fix the text.
3. tell me what you did exactly.

7.8 Create, customize and improve illustrations

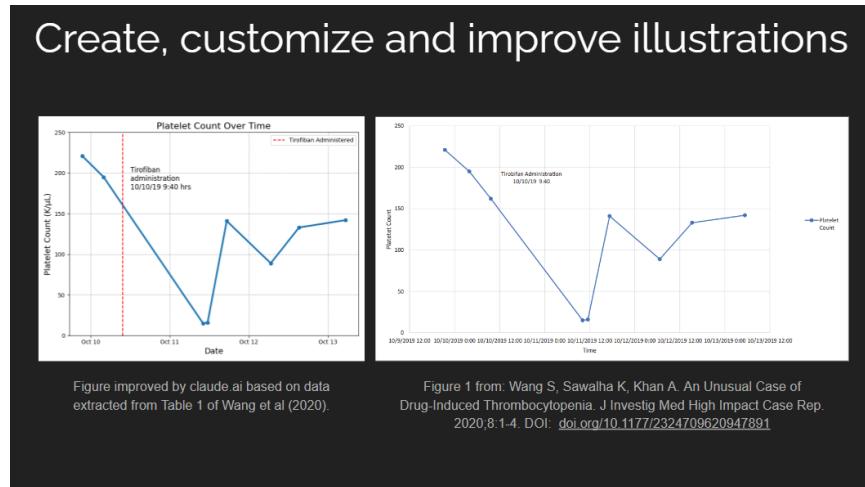


Figure 31: Slide: Create, customize and improve illustrations

This is a long example by comparison - it includes longer code blocks and some back and forth with the AI. The full conversation is here - it does not contain the plots, which are highlighted in the presentation. This experiment also shows some important differences between Claude 2 and ChatGPT regarding the workflow and the coding/plotting capabilities.

- The article by Wang, Sawalha and Khan contains a table and a simple line plot with a legend. The plot is not well readable (x-axis ticks are plotted on top of one another, for the y-label, units are missing) - which I only noticed after ChatGPT presented me with an improved plot (first comparison shown here).
- Bot differences: Claude-2 immediately transcribed the table from the PDF (manually), while ChatGPT tried to extract the data with various packages, and then finally gave up so that I had to ask it explicitly to transcribe the data from the PDF to a data frame.
- When comparing with the plot in the paper, I noticed that I overlooked the "Tirofiban Administration" on 10/10/19 at 9:hrs. I asked

the AI to add this to the plot - the AI first added a dashed vertical red line for that date (an error had to be rectified, having to do with `datetime` conversion for the `matplotlib` function). I asked to add the text and the point in red to the line plot, leading to the final plot (whole conversation online here).

- The final plot in direct comparison with the paper is shown on the slide.
- Reference: Wang S, Sawalha K, Khan A. An Unusual Case of Drug-Induced Thrombocytopenia. J Investig Med High Impact Case Rep. 2020;8:1-4. <https://doi.org/10.1177/2324709620947891> (open access PDF)

7.9 Chatting while Coding with interactive notebooks

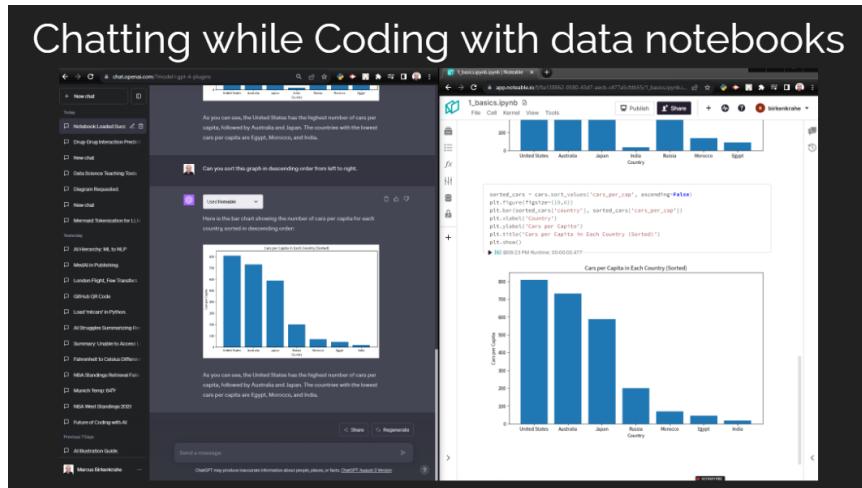


Figure 32: Slide: chat while coding with interactive notebooks

I'm leaving the best (in my world) for last: literate programming meets AI. The availability and performance of this application and plugin from noteable.io surprised and delighted me. To do this:

- Enable noteable.io plugin (requires ChatGPT plus subscription). By comparison with other online notebook apps based on Jupyter notebooks, this is actually quite nice with improved UX/UI.

- Let ChatGPT know which notebook you want to use by entering the notebook URL. Here is a demo notebook (Python) in Python that I created.
- Now, any query answer in ChatGPT will automatically be entered in the notebook. Here is my whole conversation with ChatGPT that lead to the screenshot shown on the slide, with the chat on the left, and the notebook on the right hand side (link to image).

For more on using literate programming for data science, see my recent preprint: Birkenkrahe, M. Teaching Data Science with Literate Programming Tools. Preprints 2023, 2023071847. <https://doi.org/10.20944/preprints202307.1847.v1>

7.10 Summary III



Figure 33: Slide: Summary Part III (how to use AI)

After using Claude and ChatGPT for various copy-editing tasks when writing my last paper, I asked if and how I should reference their help.

I think the answer from Claude 2 (22 July 2023) is worth sharing:

I would not recommend citing AI systems like myself (Claude), Bard, or ChatGPT in the references section of an academic paper. While acknowledging the use of AI assistance ethically in the acknowledgements is appropriate, formally citing AI systems as

references could negatively impact the perceived credibility of the work.

Some concerns with formally citing AI systems:

- They are not primary sources that directly contribute intellectual content or knowledge. The ideas in the paper should come from you as the author, with AI assisting in the communication/presentation.
- Citing them may give the impression that substantive ideas or unique data came from the AI, rather than your own research and analysis.
- As emerging technologies lacking peer review or institutional accountability, AI systems do not meet academic standards for citeable scholarly sources.
- It may raise questions about the originality of the work if AI systems are cited prominently.

Instead, I would recommend focusing your in-text citations and references on sources like:

- Relevant prior research papers from other academics
- Datasets or reports analyzed for the study
- Theoretical models/frameworks applied
- Books/articles that contextualize the topic

This helps position your work within the human scholarly community. The goal should be demonstrating the quality and originality of your own ideas, analysis, and conclusions. Citing AI could detract from that goal.

However, do note any AI assistance appropriately in the acknowledgements. The goal is transparency without giving undue credibility to the AI systems themselves. Please let me know if you have any other questions!

7.11 Attempt to predict where we're going

1. AI augmentation: scenario - Jane, a research scientist (by ChatGPT). A little euphemistic but overall doable.

An attempt to predict where we're going

- AI systems will be useful when **augmenting** rather than **automating** human tasks.
- There will be an **evolution** of models towards more **specialized** models.
- Hold on to your **humanity** by **resisting** the machine but **experiment** with it a lot.

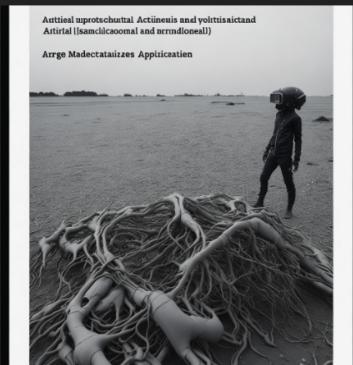


Image created by leonardo.ai with text and image prompt.

Figure 34: An attempt to predict where we're going

- **Without AI Augmentation:**

- (a) Jane spends weeks reading through dozens of research papers to understand the latest in her field.
- (b) She manually collects and analyzes data, which is time-consuming.
- (c) She writes up her findings and then seeks feedback from her peers, which can take a lot of time and back-and-forth communication.

- **With AI Augmentation:**

- (a) Research Assistance: Jane uses an AI-powered literature review tool. This tool analyzes thousands of research papers and provides her with a summarized understanding of the latest in her field in just hours.
- (b) Data Analysis: For her experiments, Jane employs an AI tool that automatically collects and preprocesses data. The tool can also point out anomalies or patterns in the data she might have missed.
- (c) Writing Assistance: As Jane writes her research paper, an AI writing assistant helps her with grammar, style, and even suggests better ways to present her data.
- (d) Feedback Loop: Before sending her work to human peers, she runs it through an AI-powered peer review simulator which

provides her with constructive feedback and potential questions or criticisms that her peers might have. This allows her to refine her work further.

- (e) Collaboration: Jane uses an AI-augmented collaboration platform that helps her seamlessly collaborate with other scientists worldwide. The platform suggests potential collaborators based on their expertise, research interests, and publication history.

In this scenario, AI doesn't replace Jane but augments her abilities, helping her to be more efficient, make more informed decisions, and collaborate more effectively.

2. Specialized LLMs: a massive list (by ChatGPT), which seems reasonable.
 - (a) Specialized Large Language Models (LLMs) are trained or fine-tuned for specific domains or tasks, enabling them to perform with greater accuracy and precision in those areas compared to general-purpose LLMs. Here are some examples:
 - (b) Medical LLMs: These models are trained on medical literature, clinical notes, research papers, and more to assist healthcare professionals in tasks like diagnosing diseases, suggesting treatments, or answering patient queries.
 - (c) Legal LLMs: Trained on law journals, case law, statutes, and legal opinions, these models can assist lawyers in drafting documents, doing legal research, or predicting the outcomes of cases.
 - (d) Financial LLMs: Models in this domain can analyze financial reports, predict market movements based on news and events, or help in risk assessment by being trained on financial data and literature.
 - (e) Scientific LLMs: These are tailored for specific scientific disciplines, like physics, chemistry, or biology. They can assist researchers in understanding complex concepts, predicting results, or doing literature reviews.
 - (f) Technical Support LLMs: Fine-tuned on technical documentation, support forums, and Q&A datasets, these models can assist in troubleshooting technical problems or guiding users through complex procedures.

- (g) Programming LLMs: Models like GitHub Copilot are trained on vast amounts of code to assist developers in writing code, debugging, or understanding complex programming concepts.
- (h) Language Learning LLMs: Tailored for language instruction, these models can provide grammatical explanations, translations, or conversational practice for those learning a new language.
- (i) Creative Writing LLMs: These can assist authors by suggesting story arcs, character developments, or even poetry and are trained on vast literature from different genres.
- (j) Historical LLMs: Trained on historical documents, books, and research, these models can provide insights into historical events, contexts, or assist in historical research.
- (k) Entertainment and Gaming LLMs: These models can be fine-tuned to assist in game design, write dialogues for characters, or even generate stories for video games.

When creating or using specialized LLMs, it's essential to ensure that biases in the training data are addressed and that the models are used ethically and responsibly, especially in sensitive domains like medicine or law.

3. How to (get or) keep up to date:

There are no shortcuts here, and ChatGPT loves pretending that there are AI-driven shortcuts.

- (a) The only way to keep tabs on AI and on your own skills is to not let them go to waste.
- (b) Only automate what you must. Often resist automation and pursue mindless drilling to keep your body and your mind nimble.
- (c) Do not substitute human communication and correspondence with the digital equivalent with machines.
- (d) Experiment as much as you can with the new tools and be brave enough to write time off if the result is not to your liking.

The machine is a stochastic mirror of the world and, the more you use it, of yourself - it won't help you grow substantially.

Good luck!