

Medical AI - How Machine Learning Can Help Your Publishing Career

White River Medical Center, Batesville AR

Marcus Birkenkrahe, Lyon College

August 8, 2023

Transcript

Poll

**Please answer a
few simple, short
questions (1 min):**



<https://tinyurl.com/wrmc-poll>

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).

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:



Figure 1: Images: unsplash.com and leonardo.ai

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 WRM.

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.

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.



Figure 2: Boy in Emerson Respirator, Nat'l Mus of Health and Medicine



Figure 3: DESY, Hamburg, Germany, 1994.

Industry



Figure 4: 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.

Teaching

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



Figure 5: UBMS class "Game and Robotics programming with Snap! and Python"

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?

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.

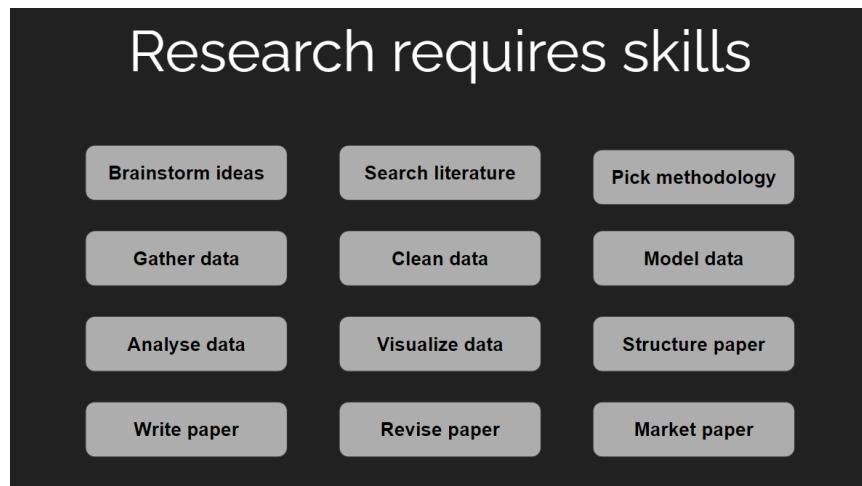
Part I: What's the problem?

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

Research requires 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 WRMC 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>

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:

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).

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.

Research writing is standardized



**Introduction
Method
Results
and
Discussion**

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 whould 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.

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)

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!

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

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

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.)

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
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).

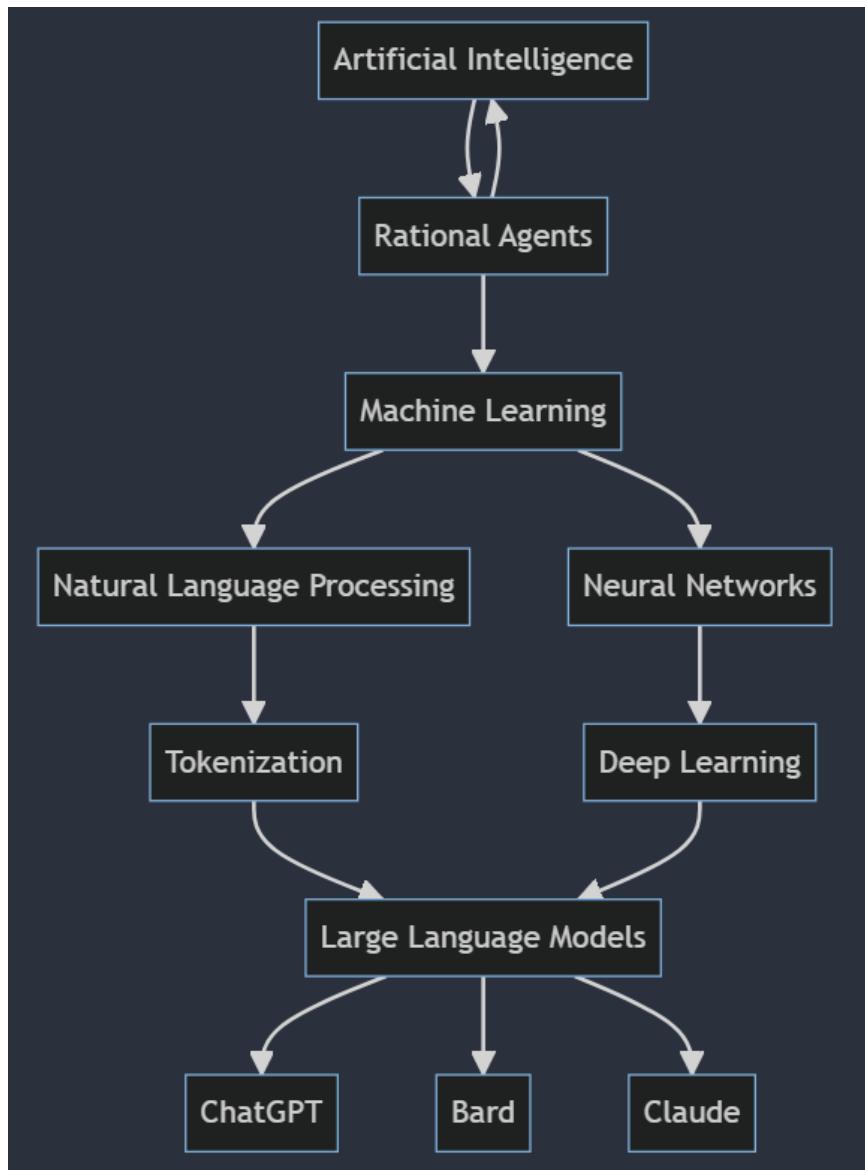


Figure 7: AI subfields (Mermaid diagram by Claude 2, my prompt)

Large Language Models (LLMs)

We'll start exploring this diagram from the bottom.

- **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."

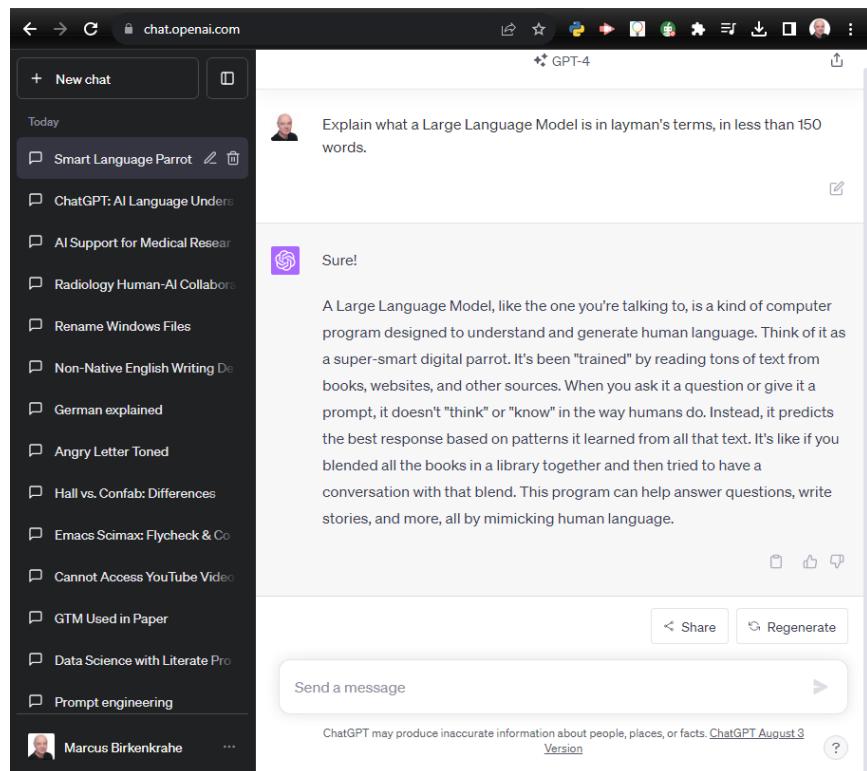


Figure 8: ChatGPT's Layman's explanation of a Large Language Model

- 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.
- "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.

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.

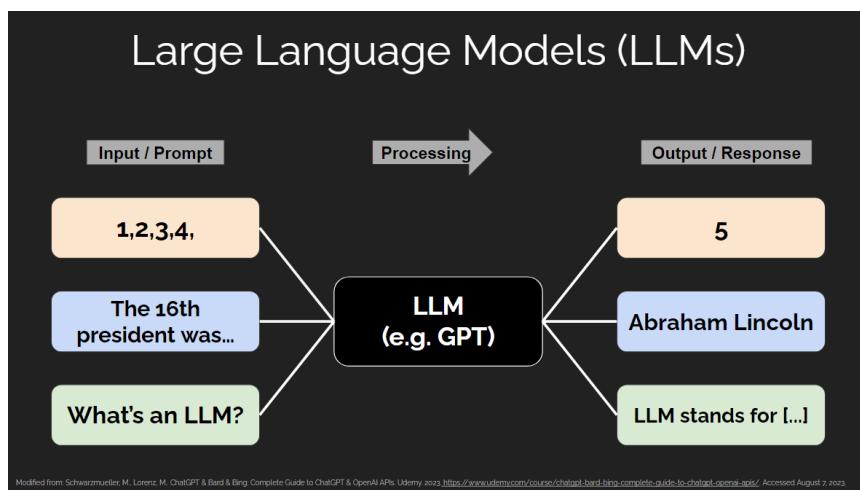


Figure 9: ChatGPT's Layman's explanation of a Large Language Model

- 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.

How are Large Language Models trained?

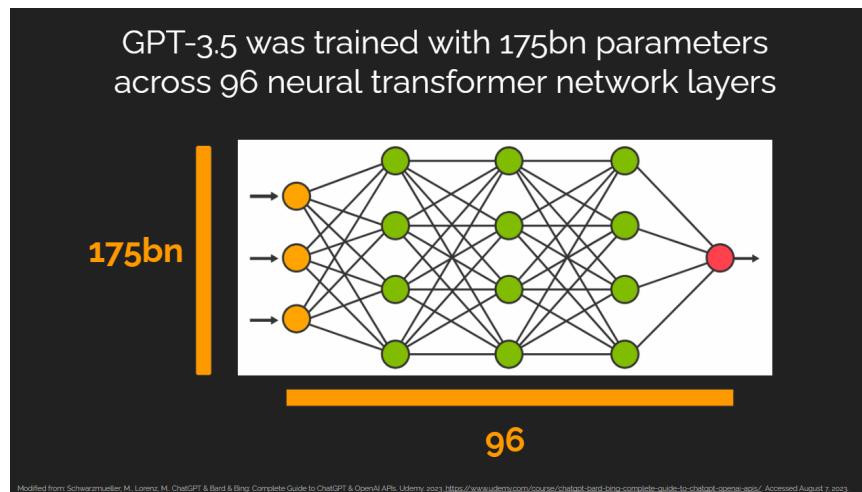


Figure 10: ChatGPT's Layman's explanation of a Large Language Model

- 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.

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.

- 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).

Part III: How can you use it?

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:

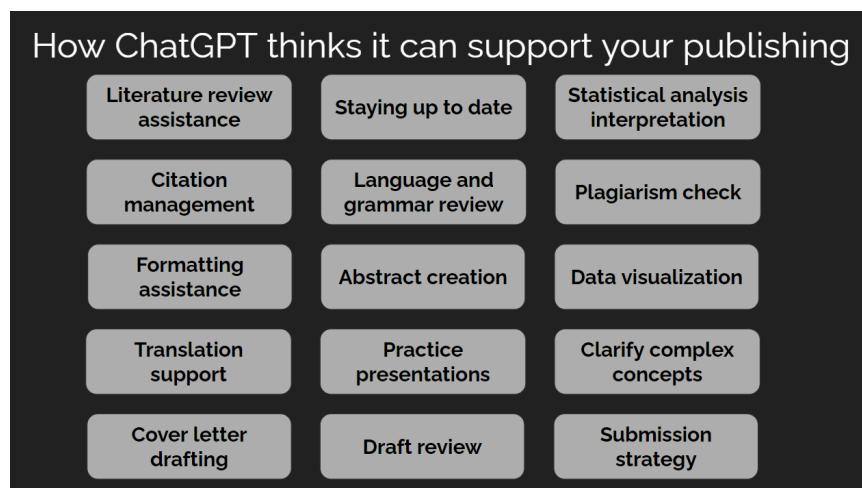
1. It is "conversational" in the sense that it remembers the conversation you had with it (for one session).
2. It is "considerate" in the sense that it tries to provide output as close to your prompts as possible (within its means).

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.

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!"

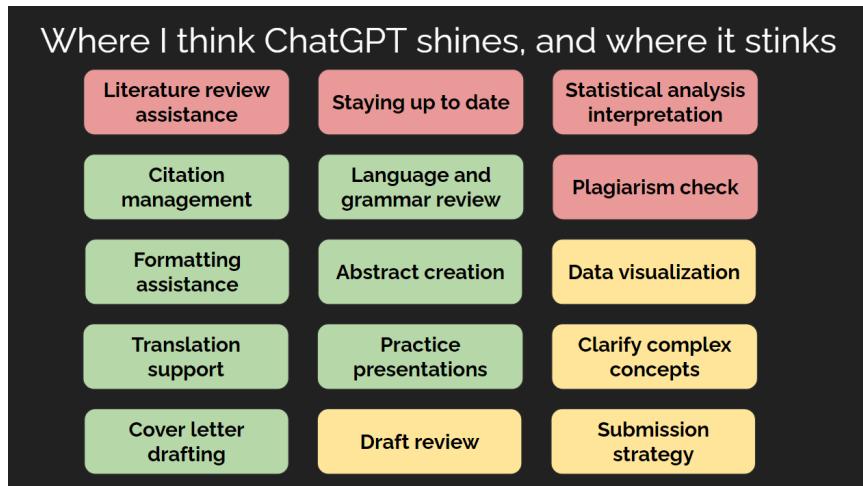
ChatGPT's response:

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.

Where I think 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. 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.

Prompt design is not Google Search

Role + Goal + Context

Figure 11: Prompt design is not Google search

Prompt design example: Twitter

Role + Goal + Context

You are an experienced data scientist and author of the article...

Goal

Write a tweet that makes people want to read the article.

Context

Paper is a follow-up case study on data science education.

Figure 12: Prompt design example: Twitter (1)

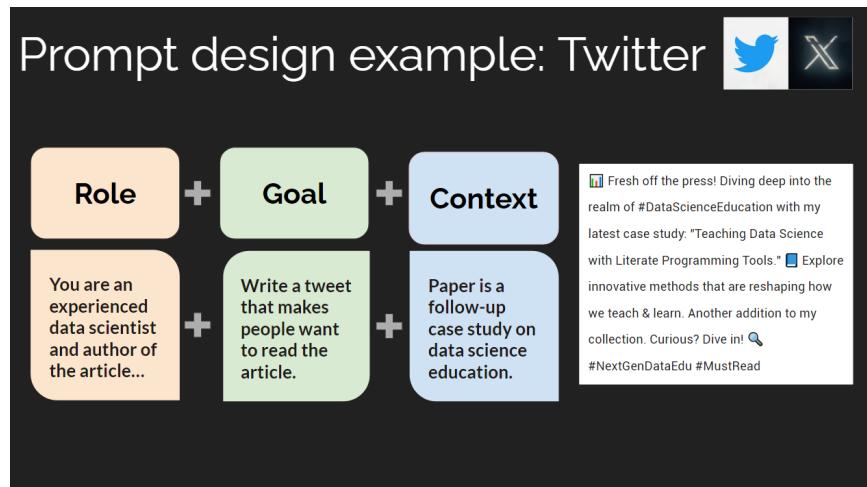


Figure 13: Prompt design example: Twitter (2)

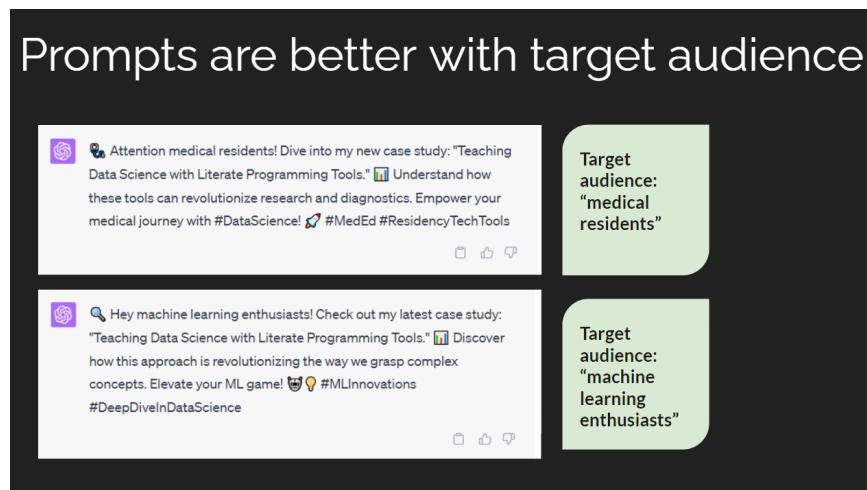


Figure 14: Prompt are better with target audience

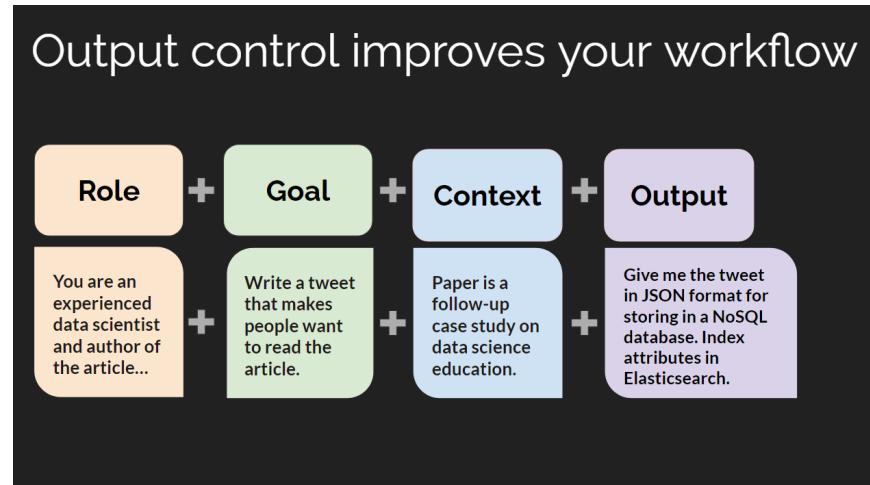


Figure 15: Response/output control improves your workflow

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",
  "hashtags": ["MLInnovations", "DeepDiveInDataScience"],
  "author": "username_here",
  "timestamp": "2023-08-07T14:05:00Z",
  "retweets": 123,
  "likes": 456
}

```

Figure 16: Tweet response/output as JSON / ElasticSearch

Prompt design / engineering

Summary III

Summary III



- **Prompt design** is not Google search
- Use **conversational** capabilities
- Text and video can be **summarized**
- **Confabulations** are always possible
- **Reference** AI assistance prudently
- AI output can only be a **starting** point