Artificial Intelligence: Can it Assist the Infection Preventionist With Surveillance?

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Objectives

- Introduce some Artificial Intelligence (AI) basics and terminologies related to infection prevention and control
- Describe use of AI in evaluating healthcare-associated infection patient scenarios in accordance with NHSN surveillance definitions
- Explore the potential uses and challenges of AI as a developing assistant to infection prevention and control programs in all settings where healthcare is delivered

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Disclosures

- Advisory Boards—Sanofi [influenza vaccine], Pfizer [meningococcal vaccine, pneumococcal vaccine, COVID-19 vaccine, Paxlovid], Moderna [COVID-19 vaccine], Valneva [travel vaccines], Seqirus [influenza vaccine], Novavax [COVID-19 vaccine]
- Speakers Bureau —Sanofi [influenza immunization], Pfizer [pneumococcal immunization, RSV immunization]
- Consultant- VaxCare [vaccination logistics]; American Hospital Association [environmental infection control]

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Some definitions

Artificial Intelligence: Computer systems that mimic human tasks that are considered to require intelligence

Generative Artificial Intelligence: AI that generates some new content – Language models for text, others for video, audio, etc.

Machine learning (ML): a set of algorithms that can be used to recognize patterns in data and predict similar patterns with new data – one method of achieving artificial intelligence

Deep learning (DL): a machine learning approach using an artificial neural network with many hidden layers

Training: the process of creating a ML model

Testing: the process of supplying new data to the trained ML model to check its performance

Supervised learning: ML models that recognize patterns in data and link those patterns with a previously documented outcome

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Outline

Basics of Generative AI

Ethics and Other Concerns

Current Applications

Future Applications

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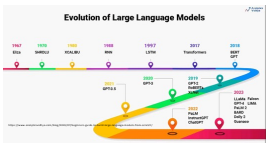
Basics of Generative Artificial Intelligence

- GenAI is not new
- Generative means to create something
- Create new
  - Text
  - Audio
  - Video
  - Data
  - Code
  - …



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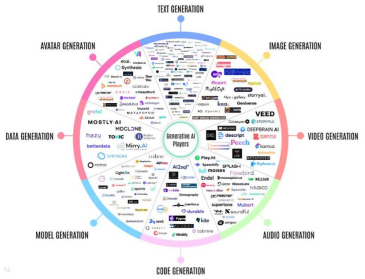
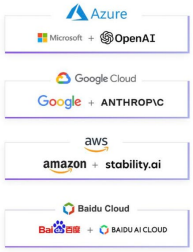
Basics of Generative Artificial Intelligence





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Building AI

Models are trained

Using data similar to what you want as an output

For example, large amounts of text are used to train Large Language Models

Many images are used to train text to image AI

Models are tested

Testing reports how 'good' the model is at producing the gold standard output

Can be based on many metrics, including human curation

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Large Language Models (GPT-4, Claude, Llama)

- Generative AI that is focused on text-to-text
- Submit a 'prompt' and the model reports an 'answer'
- Uses transformer architecture to map words to numbers and deep learning to predict the most likely 'next word'
- Vectors of numbers represent the underlying meaning and structure of words – and a computer can understand them
- When a prompt is typed, it is decomposed to numbers and probability distributions are created - the model selects the next most likely word from what it has seen historically in training

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LLMs do not simply look up information and regurgitate it.

They piece together words that they have seen in their training based on probabilities.

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Making LLMs better

- Foundational models like GPT-4, Claude, and Llama are general
- They are great at predicting the next word in a general conversation
- They are not good for specialized tasks
- How do we make them work for our tasks?

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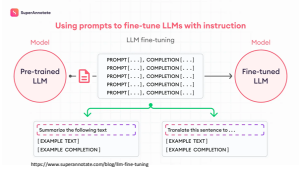
Making LLMs better: Fine Tuning

- Many different approaches
- In general, take a foundation model and re-train it with very specific data
- Now it knows how to respond, but specifically knows how to respond in your area of interest
- Issue: static



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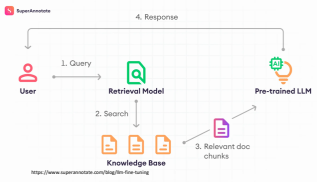
Making LLMs better: Retrieval Augmented Generation (RAG)

- Many different approaches
- In general, take a foundation model and add specific knowledge bases for it to see on the fly
- Response is likely just as good as fine tuning
- Not static, cheaper, faster



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Foundation models are only as good as the data used for training

garbage in = garbage out

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Limitations and ethical concerns

Limitations in understanding context and context-dependent meaning:

While language models like GPT-4 can generate human-like responses, they can struggle to understand the context in which a question is being asked.

Answers are created based on patterns in the training data. They are not answers developed from context and underlying meaning/knowledge/understanding.

LLMs are not sentient.

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Limitations and ethical concerns

Bias in training data:

The training data used to train these models can contain biases and stereotypes. As a result, these biases can be reflected in the responses generated by the model, which can perpetuate harmful stereotypes and reinforce societal inequalities.

For example, if a model is trained on predominantly male-authored text, it may generate responses that reflect gender bias.

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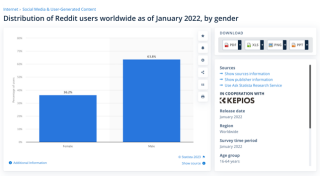
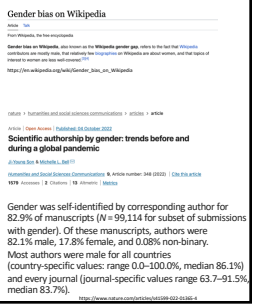
Biases



https://www.statista.com/statistics/1255582/distribution-of-users-on-reddit-worldwide-gender/



Gender was self-identified by corresponding author for 82.9% of manuscripts ($N = 99,114$ for subset of submissions with gender). Of these manuscripts, authors were 82.1% male, 17.8% female, and 0.08% non-binary.

Most authors were male for all countries (country-specific values: range 0.0–100.0%, median 86.1%) and every journal (journal-specific values range 63.7–91.5%, median 83.7%).

https://www.nature.com/articles/s41599-022-01360-6

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Biases

Algorithm bias:

The algorithms used to build large language models can also introduce biases into the model's outputs. For example, the algorithms may be designed *to prioritize certain types of information* or to make certain assumptions about the relationships between words and concepts.

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Biases

Societal bias: Large language models can *also reflect broader societal biases and stereotypes*, such as racial and gender biases. These biases can be amplified by the models or amplified by the platform giving rise to the text.

https://www.theatlantic.com/technology/archive/2022/02/facebook-hate-speech-misinformation-superusers/621617/

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Who chooses what is right and wrong?

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Limitations and ethical concerns

Privacy concerns:

Large language models like GPT-4 are often trained on vast amounts of personal data, raising concerns about privacy and the protection of personal information.

Your data, if posted on the internet, may be used in training.

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Machine Learning in IP – not so much AI

- Much discussion, but little AI application in IP
- However, there has been much ML application over the past decade to predict HAIs
- Natural language processing (NLP) and text mining is also commonly used to extract structured data from unstructured text

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Contents lists available at ScienceDirect

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Major Article

Assisting the infection preventionist: Use of artificial intelligence for health care–associated infection surveillance

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Key Words:
Machine learning
AI agent
GPT
Mistral
Case definition

Background: Health care–associated infection (HAI) surveillance is vital for safety in health care settings. It helps identify infection risk factors, enhancing patient safety and quality improvement. However, HAI surveillance is complex, demanding specialized knowledge and resources. This study investigates the use of artificial intelligence (AI), particularly generative large language models, to improve HAI surveillance.
Methods: We assessed 2 AI agents, OpenAI's chatGPT plus (GPT-4) and a Mixtral 8×7b-based local model, for

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Our Methods Approach

- We used both ChatGPT (build your own GPT within GPT-4) and the open source Mixtral 8x7b models [current versions available at the time of the study] as the basis for our project
- The curated CDC Patient Safety Component Manual, now a readable document for RAG, was added to those 2 AI models. This curated document helped the models better understand the approach it should take for writing responses
- Models were prompted with a simple request of "is this an HAI: {input the de-identified case information}" and the models wrote the answer.
- Scenarios were developed with varying levels of scenario complexity.

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Results

- Both agents produced 100% accurate responses for both CLABSI and CAUTI for all three levels of complexity after clear prompting.

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CLABSI Cases (Level 1):

- On March 2 Mrs. Dis N. Fect is admitted to the medical unit with severe abdominal pain and fever. On March 4 her white blood count (WBC) increased and chills were documented. On March 4 the patient had a central line placed and blood cultures were collected, with *Staphylococcus aureus* identified in one of two blood culture bottles. No other source of infection is identified.
- **Question:** Is this a CLABSI?
- **Accepted Answer:** No, the eligible central line is not in place for more than 2 consecutive calendar days on the BSI date of event or before.

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HAI Assist Answer:

- **Jan 3, 2024:** Based on the information provided and the criteria for Central Line-Associated Bloodstream Infection (CLABSI) from the provided documents, this case does not qualify as a CLABSI. For a CLABSI, the central line must have been in place for more than two consecutive calendar days during the current admission.
- In Mrs. Dis N. Fect's case, the central line was placed on March 4, the same day the blood cultures were collected and *Staphylococcus aureus* was identified. Since the central line was not in place for more than two consecutive calendar days when the blood culture was collected, it does not meet the criteria for a CLABSI.

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Template for assessing a case for central line-associated bloodstream infection:

- Is this a laboratory-confirmed bloodstream infection for the adult patient include (LCBI 1 or LCBI 2), mucosa barrier injury laboratory-confirmed bloodstream infection (MBI-LCBI), or central line-associated bloodstream infection (CLABSI), or a secondary bloodstream infection?
- It is often better to only ask a single question to avoid model confusion, so this may be broken out into asking specifically about a CLABSI or a second request for a secondary bloodstream infection. All dates should be written in full text with month, day, and year.
- Add all dates specific with the information the date is linked to instead of stringing together multiple things that happened on the same date (e.g. YES: March 2, 2024 the patient was admitted to the hospital. March 2, 2023 a triple lumen catheter was inserted. NO: March 2, 2024 the patient was admitted and a triple lumen catheter was placed). Do not use abbreviations.

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Template for assessing a case for central line-associated bloodstream infection:

Minimum information to include:

- Patient age
- Date of current facility admission
- Date of central line insertion
- Date of central line removal
- Symptoms, including localized symptoms at insertion site
- Date of onset of symptoms
- Date of laboratory test(s)
- Laboratory test result(s)
- Date of a prior bloodstream infection during current admission

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What We Learned

- AI has a role in assisting Infection Preventionists with surveillance
- Since these models do not integrate with patient information [this project not designed to do this], the role of AI is focused in assisting the IP with identification of HAI through a learning process
- Use of AI to evaluate patient scenarios using AI may be of assistance with CAUTI and CLABSI surveillance
- Curation of the surveillance definitions is time consuming but a critical element in the process
- AI models provide rationale information that may also be used for education and training

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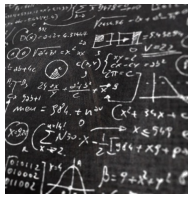
What's Next

- Next step may include other HAI surveillance elements including SSI, VAE, and lab identified events; addressing situations for use of PPE and Expanded Barrier Precautions
- Development of a surrounding education program to determine how to use AI for training
- Cadence of updating surveillance definition information so AI model uses current material
- Performance of exploratory studies using currently versions of existing agents [e.g., what updates have been done to the baseline mathematics of the agents]



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Future applications

- Completely automated surveillance from the EMR
- Surveillance from video
- Image surveillance (Surgery, hand hygiene)
- Education (text to video)

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The future is here…
and Gemini has only been available for 5 months.

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Thanks for your time!

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