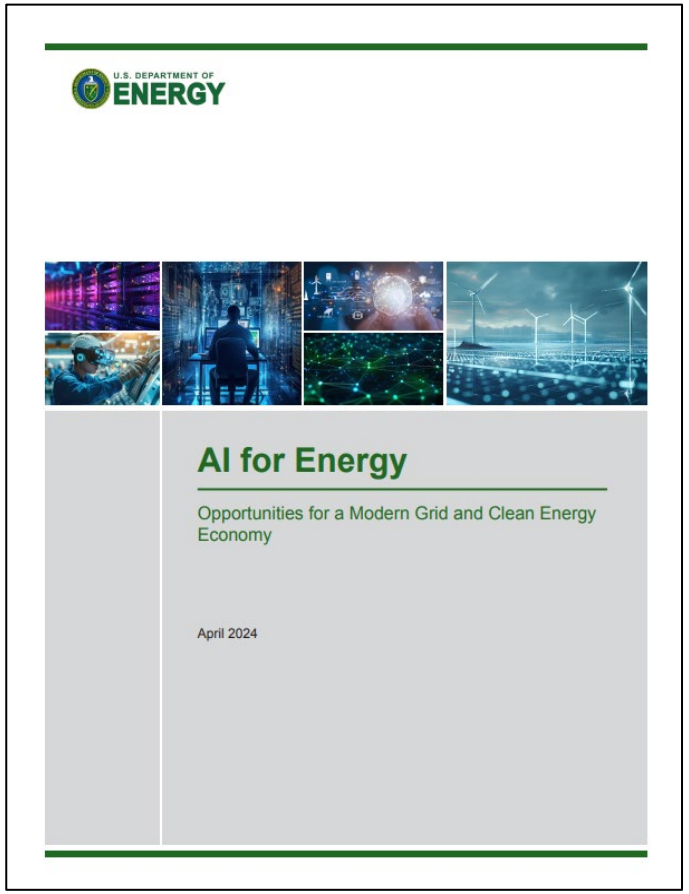
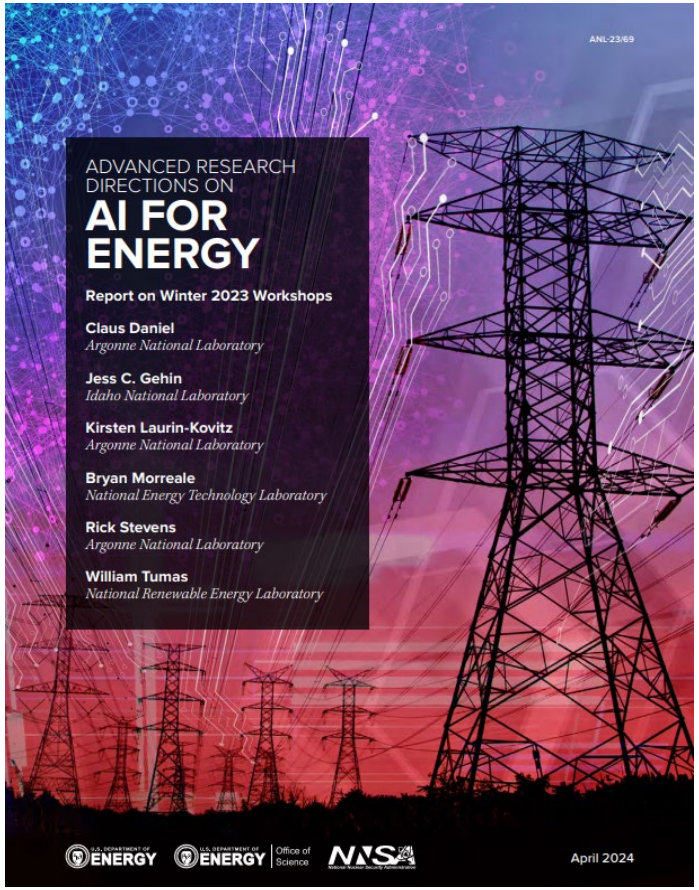
Enhancing NEPA Practice with AI: Tools, Ethics, and DOE's PolicyAI Framework

Keith J. Benes
Senior Advisor – DOE Office of Policy

December 9, 2024

DEPARTMENT OF ENERGY AND NATIONAL LABORATORIES ARE LEADERS IN ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING





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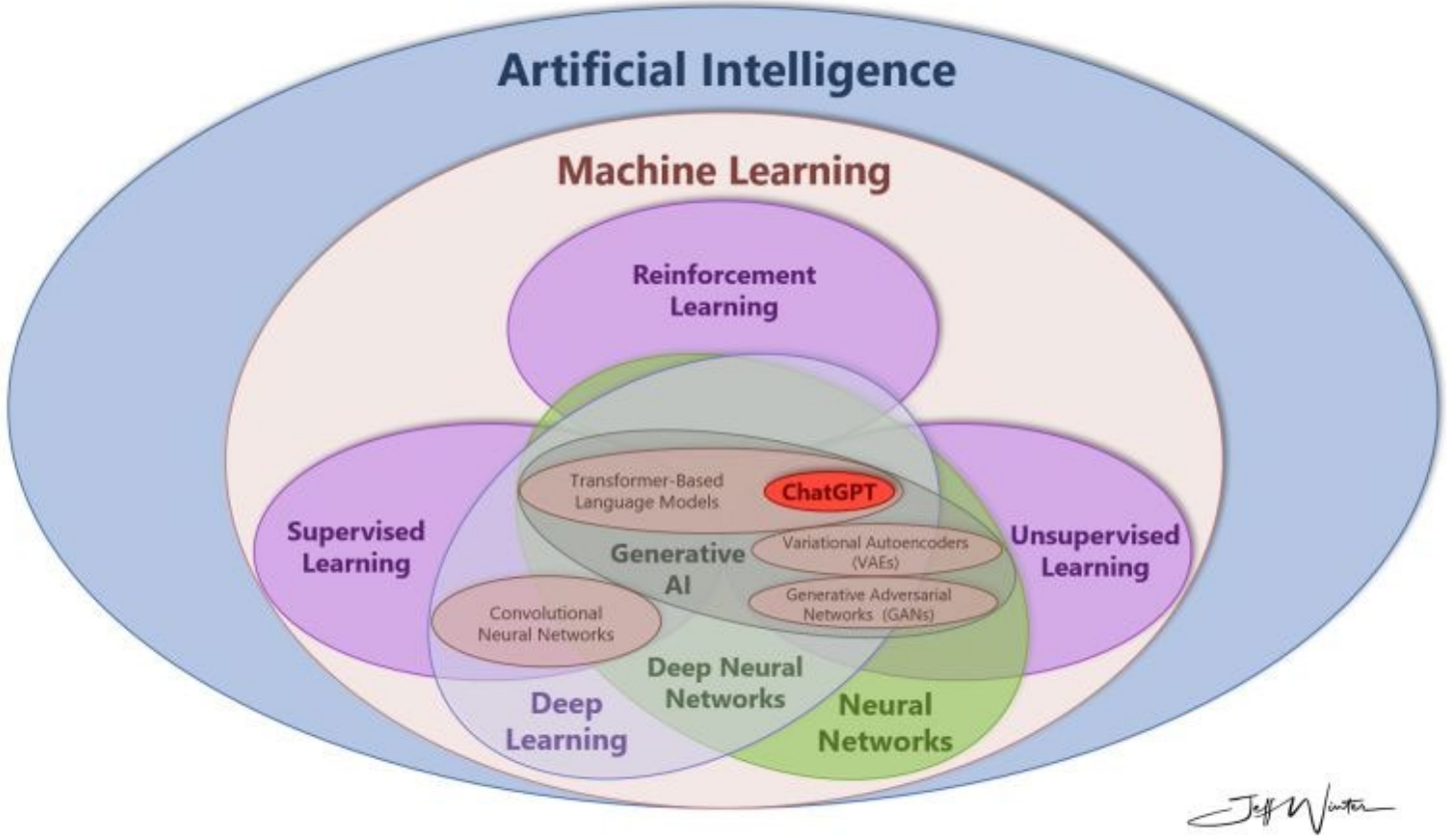
DOE and the Labs Published Two Reports on AI for Energy in April 2024

- DOE Report focused on near-term use cases
- Labs' "Advanced Research Directions" structured around 10-year grand challenges

WHAT IS ARTIFICIAL INTELLIGENCE?

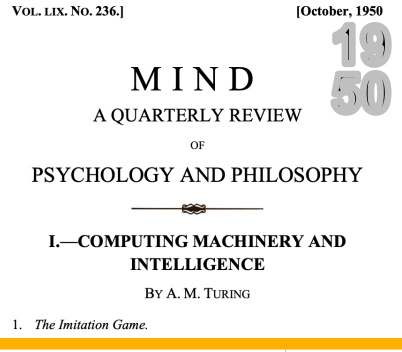
- 15 U.S.C. 9401(3): a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. Artificial intelligence systems use machine- and human-based inputs to perceive real and virtual environments; abstract such perceptions into models through analysis in an automated manner; and use model inference to formulate options for information or action.
- Non-Machine Learning AI:
  - Symbolic AI
  - Search
  - Optimization
  - Expert Systems

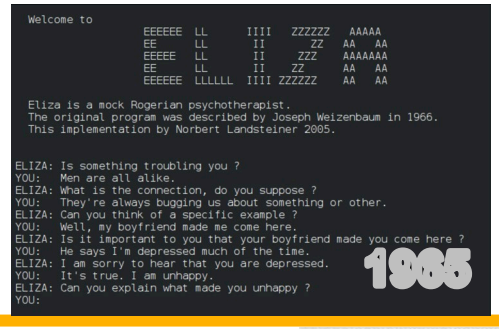


A BRIEF HISTORY OF ARTIFICIAL INTELLIGENCE

PERCEPTRON TESTED

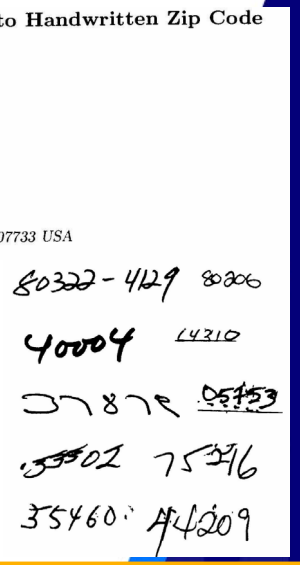
An early artificial neural network enabling pattern recognition.





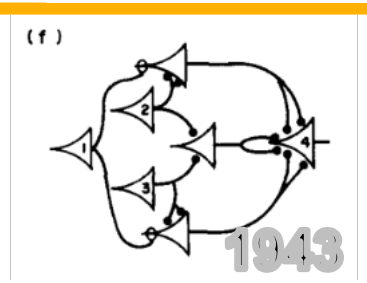
EXPERT SYSTEMS

Expert systems tried to emulate human decision making by combining a knowledge base with a pre-defined set of "if-then" type rules for inference.

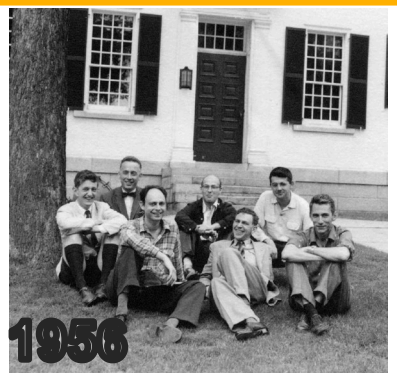


BACK PROP. APPLIED

Successfully use to Demonstrate training a neural network to Recognize hand-written Zip codes

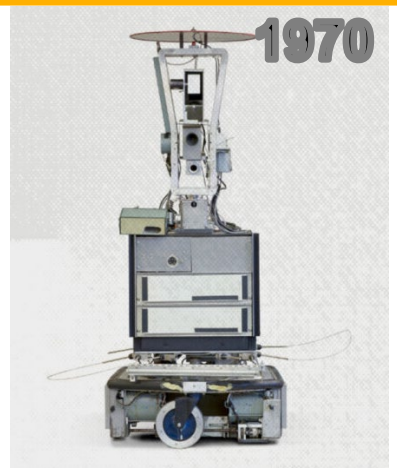


"A Logical Calculus of the Ideas Immanent in Nervous Activity"



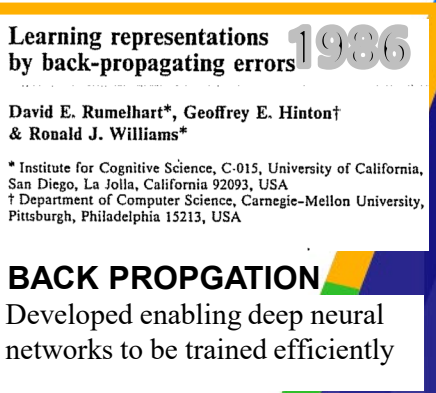
DARTMOUTH AI CONF

AI as a field of study Is launched, coined the term "Artificial Intelligence"



SHAKEY THE ROBOT

The first general purpose mobile robot. Many innovations in robotics, computer vision, and natural language processing trace back to Shakey



BACK PROPGATION

Developed enabling deep neural networks to be trained efficiently

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A BRIEF HISTORY OF ARTIFICIAL INTELLIGENCE

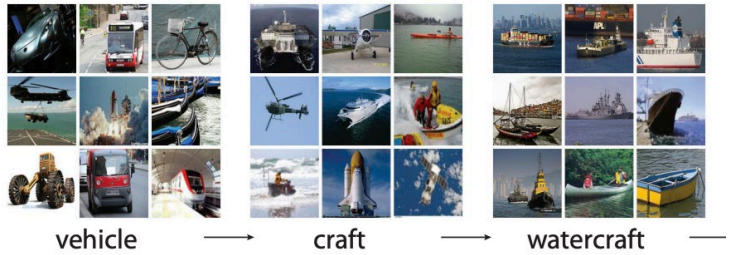
ALEXNET WINS IMAGNET CHALLENGE

ImageNet had 12 million labeled images across 22,000 categories and held and annual competition.
The AlexNet team successfully used a deep-learning to achieve error rate 10% lower than nesecond place.

ImageNet: A Large-Scale Hierarchical Image Database

2012

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li and Li Fei-Fei
Dept. of Computer Science, Princeton University, USA
{jiadeng, wdong, rsocher, jial, li, feifeili}@cs.princeton.edu



Attention Is All You Need

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2017

Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.0 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature.

Google Researchers Introduce the Transformer Architecture underlying Many leading Large Language Models

2004 DARPA SELF-DRIVING GRAND CHALLENGE

No vehicles finish
150 Mile Course

ALPHAGO - 2016

Google Deepmind AlphaGo defeats world champion Lee Sedol

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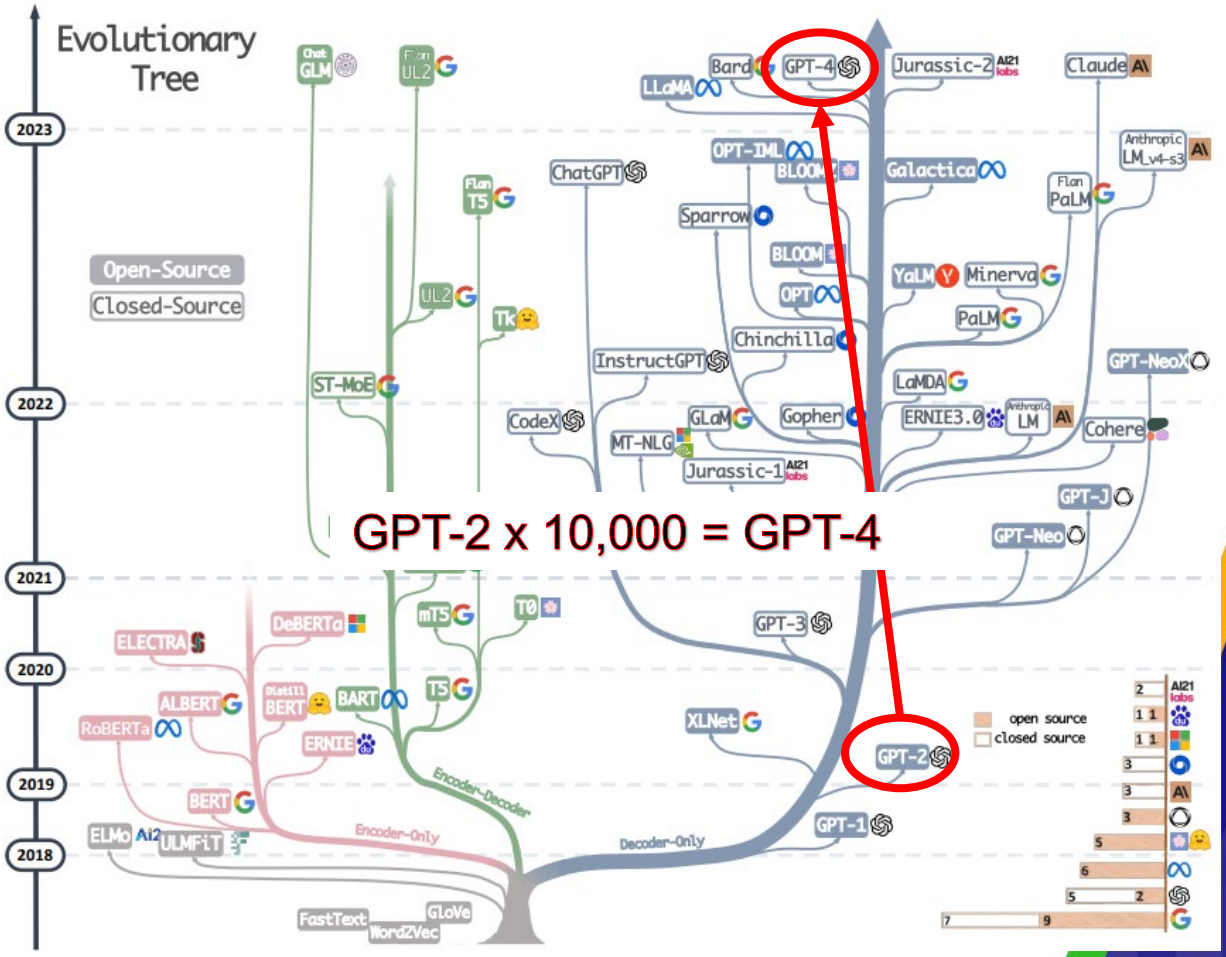
A BRIEF HISTORY OF AI – LARGE LANGUAGE MODELS

- Since the introduction of the Transformer architecture, large language models built with that approach have dominated research budgets and public attention
- The basic algorithms and theories have been around for decades, the current factor driving innovation is the massive amount of compute and data
- For example,
  - to make the jump from GPT-2 to GPT-3 compute increased 100 times
  - GTP3 to GPT-4 compute increased 100 times more



Harnessing the Power of LLMs in Practice: A Survey on ChatGPT and Beyond (arxiv.org)

A BRIEF HISTORY OF AI HYPE

1956: Herbert A. Simon

- (Economist and Cognitive Scientist, Dartmouth Conference Co-founder) *Prediction*: "Machines will be capable, within 10 years, of doing any work a man can do."

1965: Herbert A. Simon

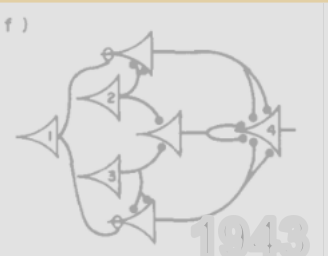
- (Nobel Prize-winning AI pioneer) *Prediction*: "Machines will be capable, within twenty years, of doing any work a man can do."

1970: Marvin Minsky

- (MIT AI Lab Co-founder) *Prediction*: "In from three to eight years we will have a machine with the general intelligence of an average human being."

1984: John McCarthy

- (Computer Scientist, AI Pioneer) *Prediction*: "Within a decade, machines will be capable of doing many tasks currently requiring human intelligence."



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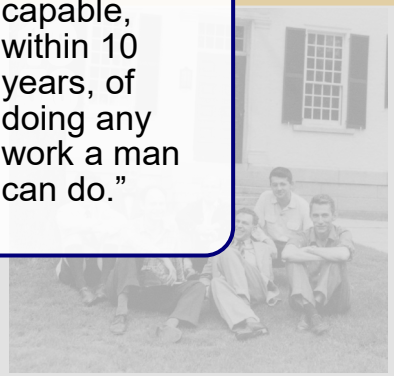

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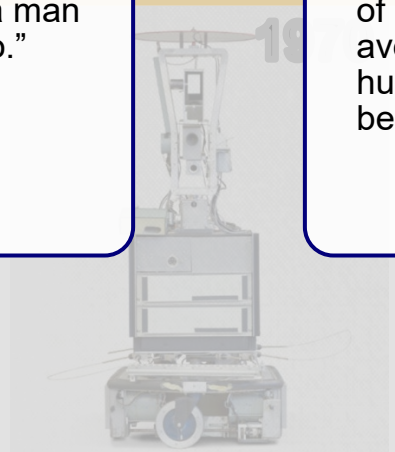

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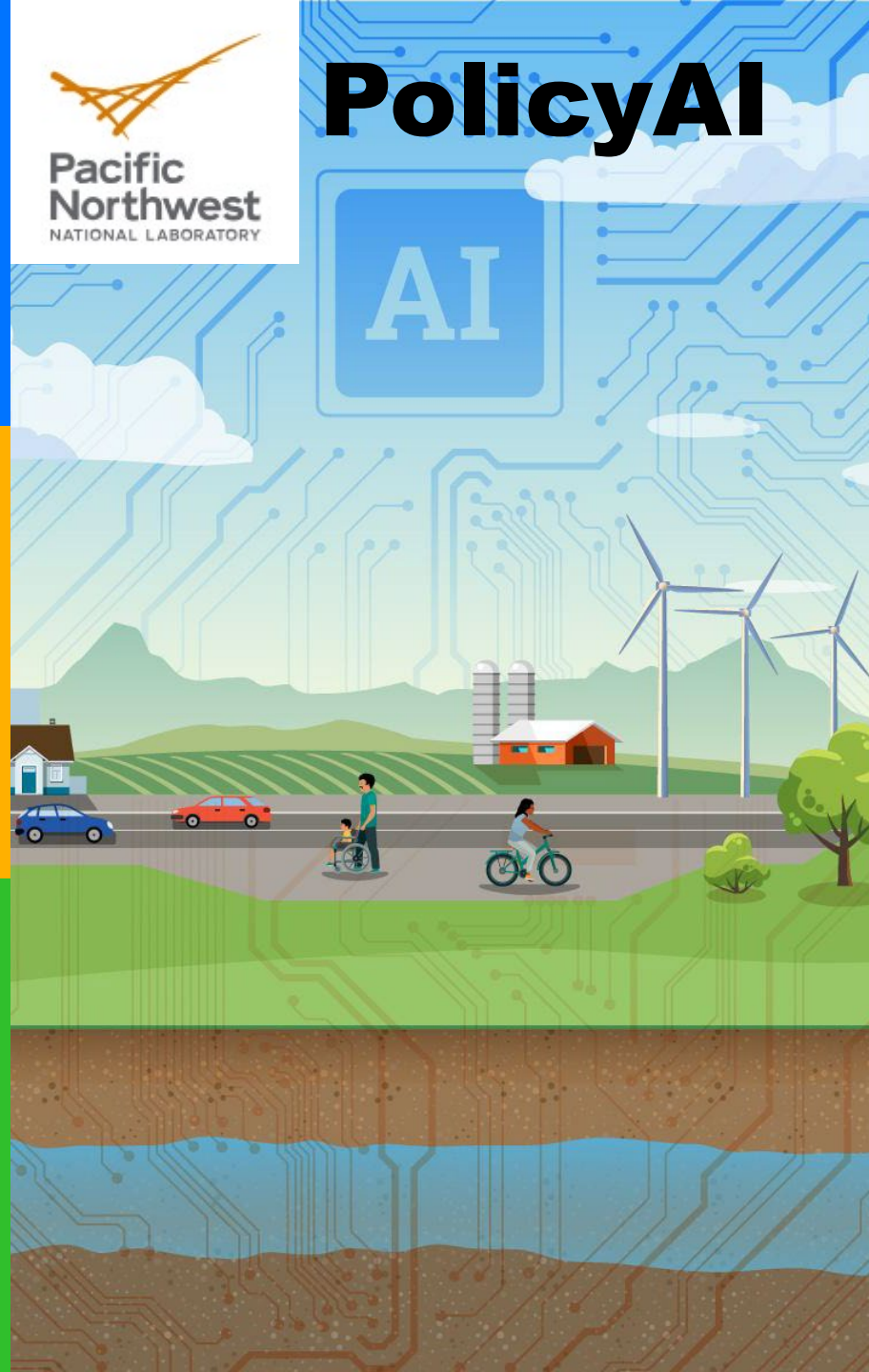
DOE voltAIc Initiative - Overview

- DOE is investing in RDD&D on AI capacity to address variety of siting and permitting challenges for clean energy infrastructure at the federal, state, local, and tribal levels
- The initiative will include multiple workstreams leveraging:
  - Expertise of DOE labs
  - Extensive cooperation with the White House and federal agency partners
  - Cooperation with industry partners, NGOs, philanthropy and academic institutions
  - Outreach to state, local, and tribal authorities through coordination with other DOE programs and initiatives such as EERE's R-STEP
- Federal Permitting Council is providing support to enable DOE to expand work with federal interagency partners beyond core DOE mission areas
- Main focus is on developing tools for government officials, but will also create publicly available data sets and open-source models that can be utilized by anyone
- Anchor project: PNNL Policy AI



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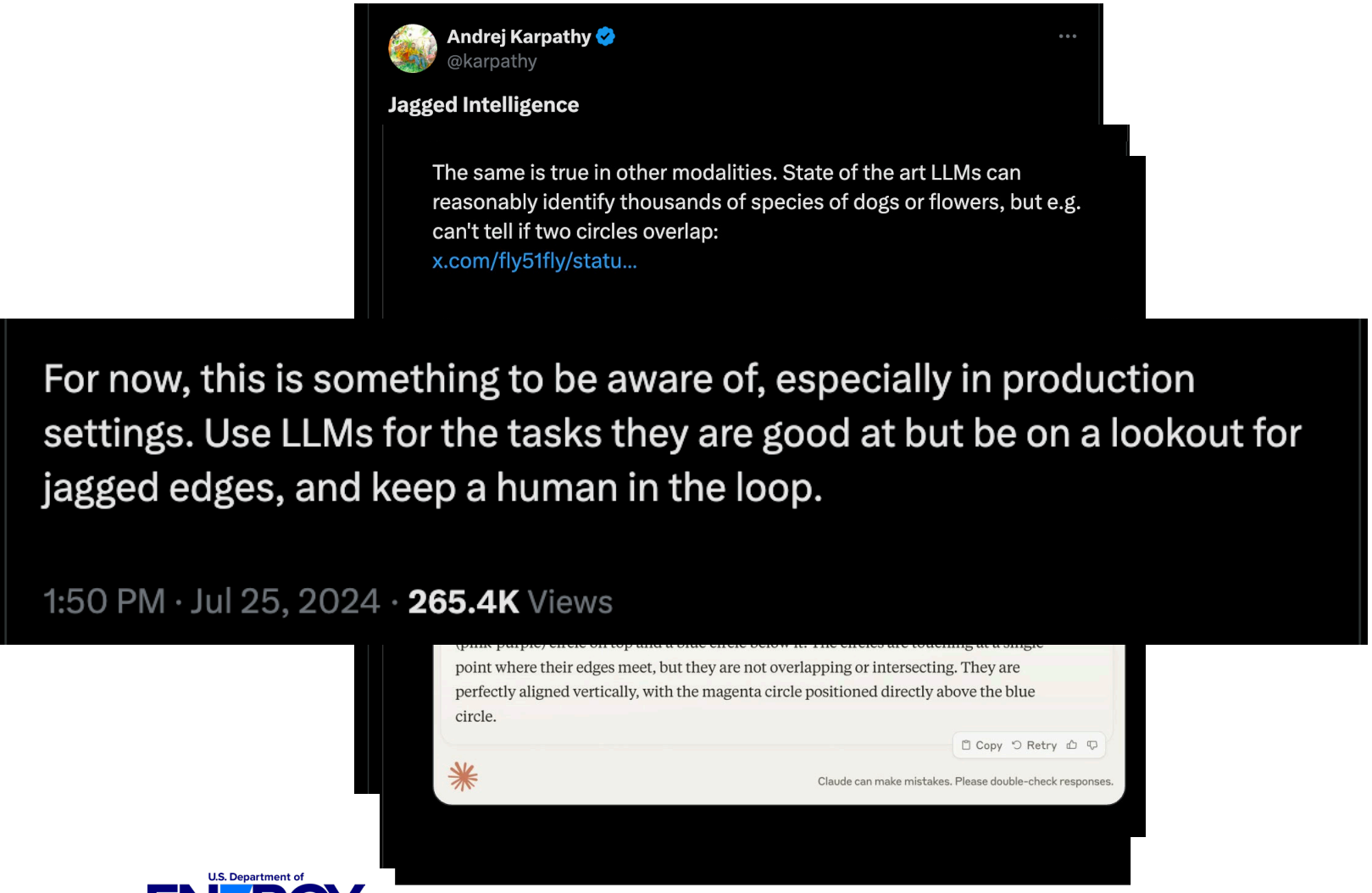
LLMS DISPLAY “JAGGED INTELLIGENCE”



OpenAI GPT-4 Performance on Standardized Tests March 2023 Estimated Percentile	
Uniform Bar Exam	~90th
LSAT	~88th
GRE – Quantitative	~80th
GRE – Verbal	~99th
GRE – Writing	~54th
Medical Knowledge Self-Assessment	~74th
Certified Sommelier	~86th

https://openai.com/index/gpt-4-research/

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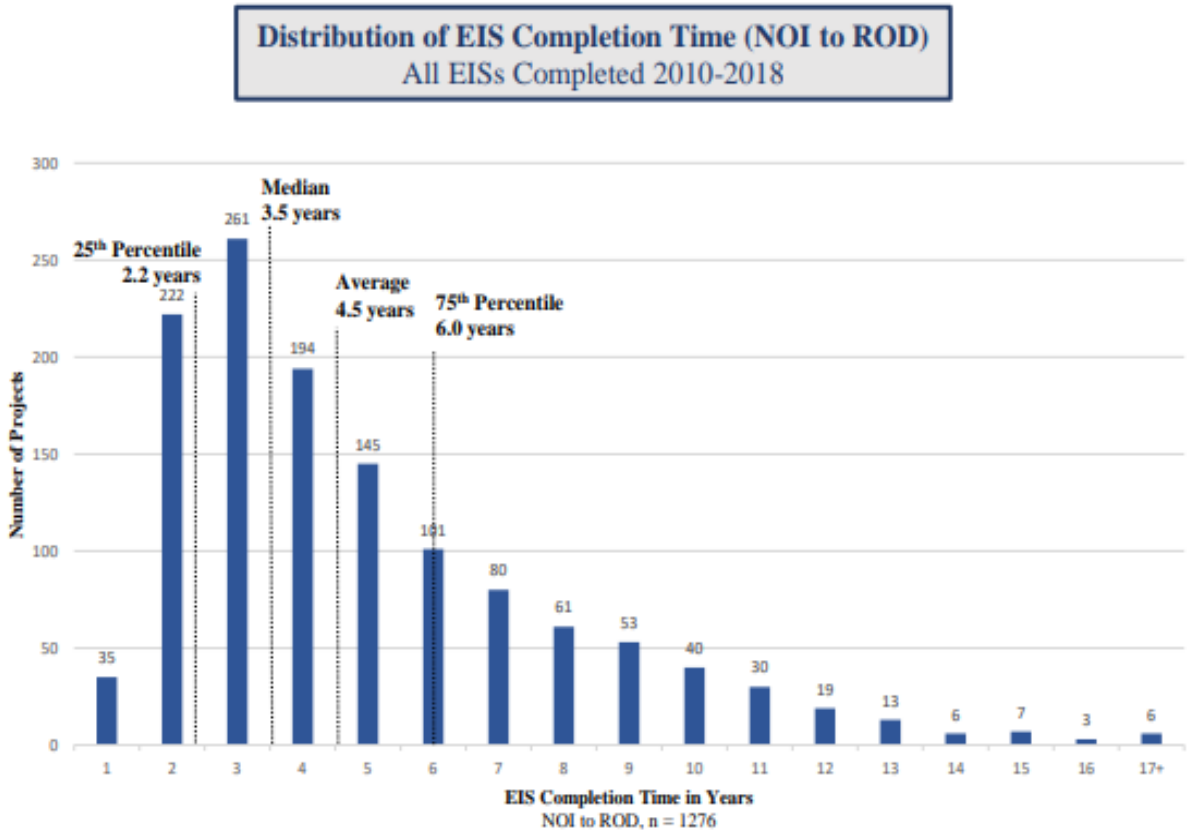
COMMON CRITICISM: NEPA REVIEWS TAKE TOO LONG

- It takes 8 to 10 years to build interstate transmission lines
- Federal Environmental Impact Statements take and average of 4.5 years to complete
- Other “shorter” NEPA reviews can be highly variable and unpredictable

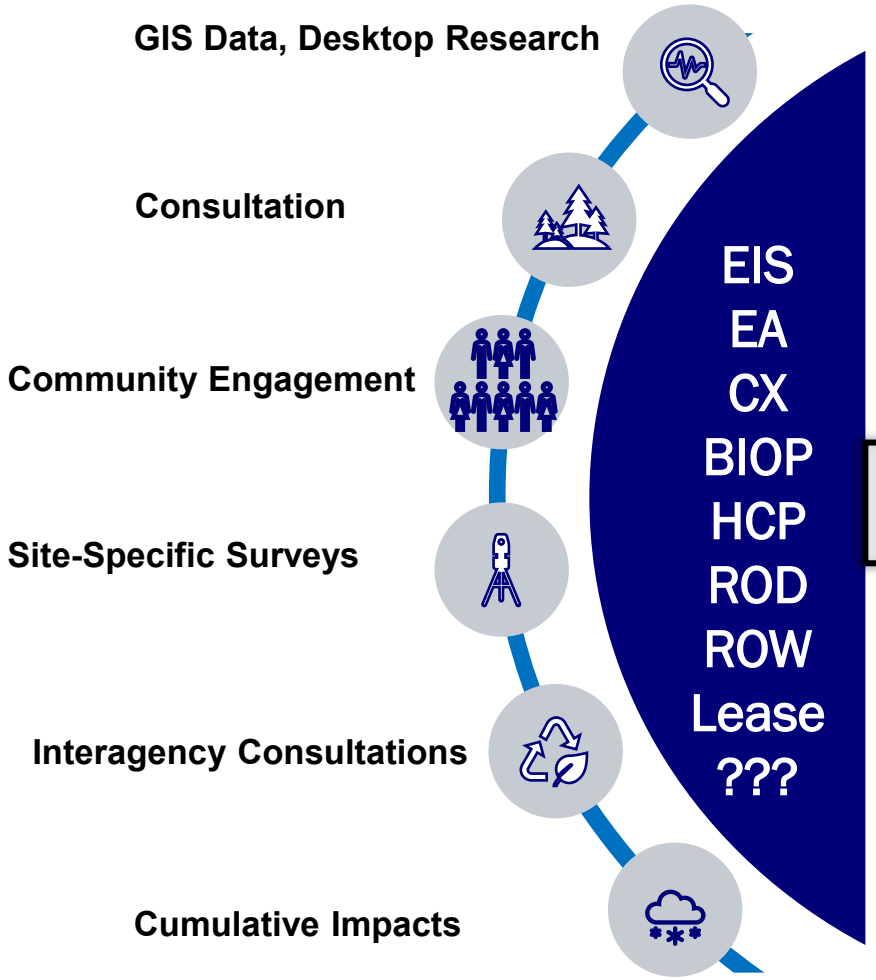
USFS Data Indicates Other Factors Other Than NEPA Requirements Drive NEPA Review Times

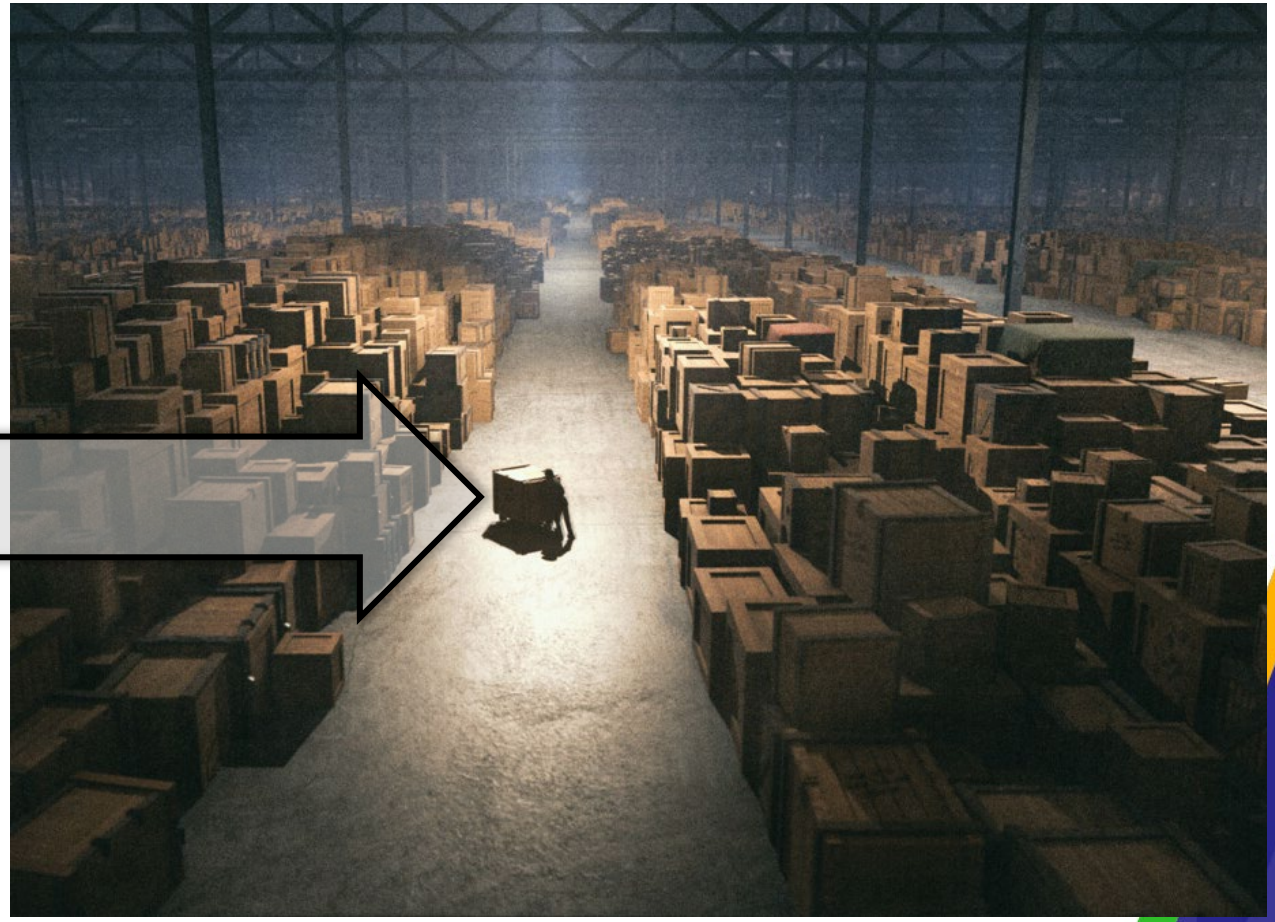
	5th	25th	50th	75th	95th
CX	19	54	112	245	714
EA	91	235	445	779	1,765
EIS	294	595	1,007	1,585	3,020

Source: Ruple, et al. 2022



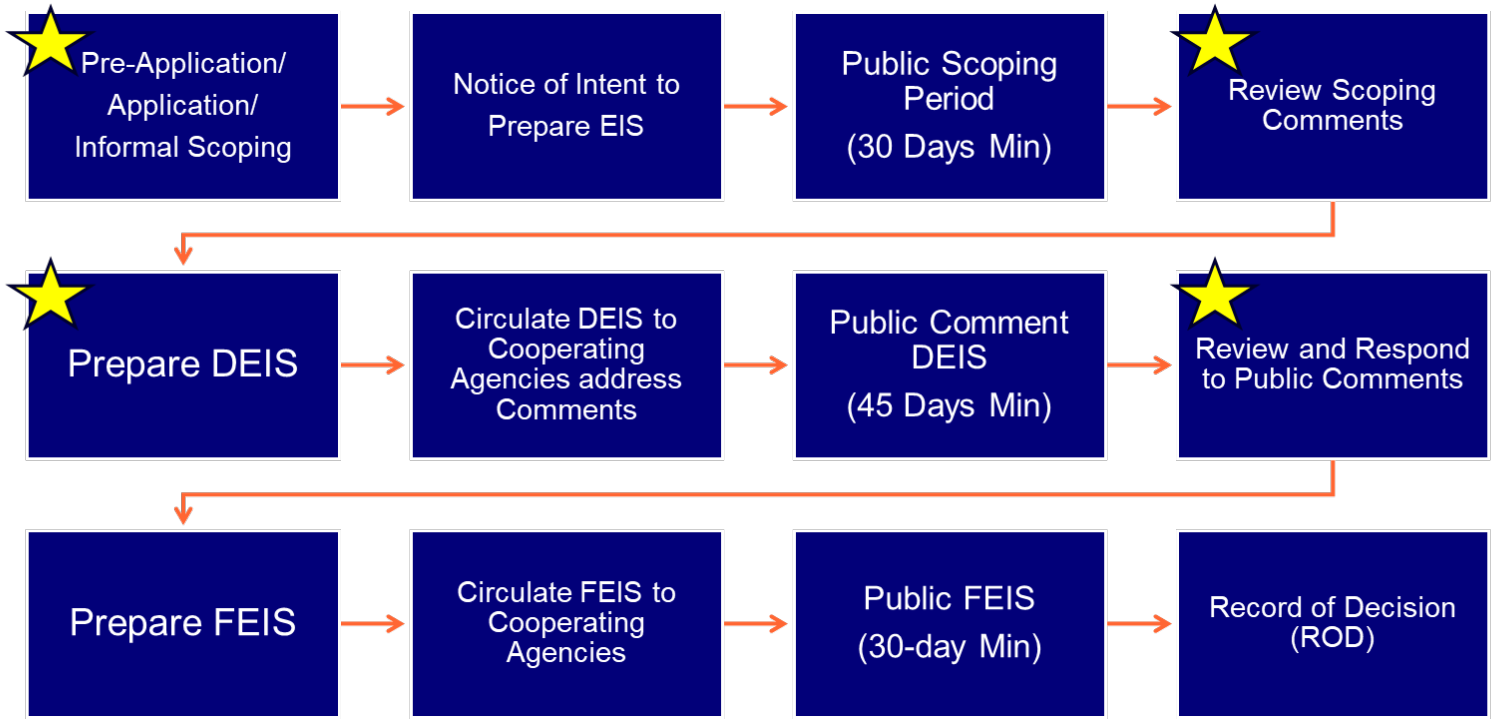
PERMIT REVIEWS PRODUCE LARGE AMOUNTS OF UNSTRUCTURED DATA THAT IS TYPICALLY USED ONCE AND FORGOTTEN





Still from: Spielberg, Steven, director. Raiders of The Lost Ark. Paramount Pictures. 1981

RISK-BASED APPROACH INTEGRAL TO DEVELOPING POLICYAI PROJECT



PolicyAI Project Designed to Focus on Lower-Risk Uses

- Only public documents in data set
- Models do not incorporate queries
- Prioritize stages of workflow with multiple human (and public) checks before decisions are made

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POLICYAI IS COMPLIANT WITH FEDERAL GUIDANCE

PolicyAI is compliant with guidance for the use of generative AI across federal agencies:

- Executive Order 14110: Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence
- Office of Management and Budget (OMB): M-24-10-Advancing-Governance-Innovation-and-Risk-Management-for-Agency-Use-of-Artificial-Intelligence
- Department of Energy (DOE): Department of Energy Generative Artificial Intelligence Reference Guide

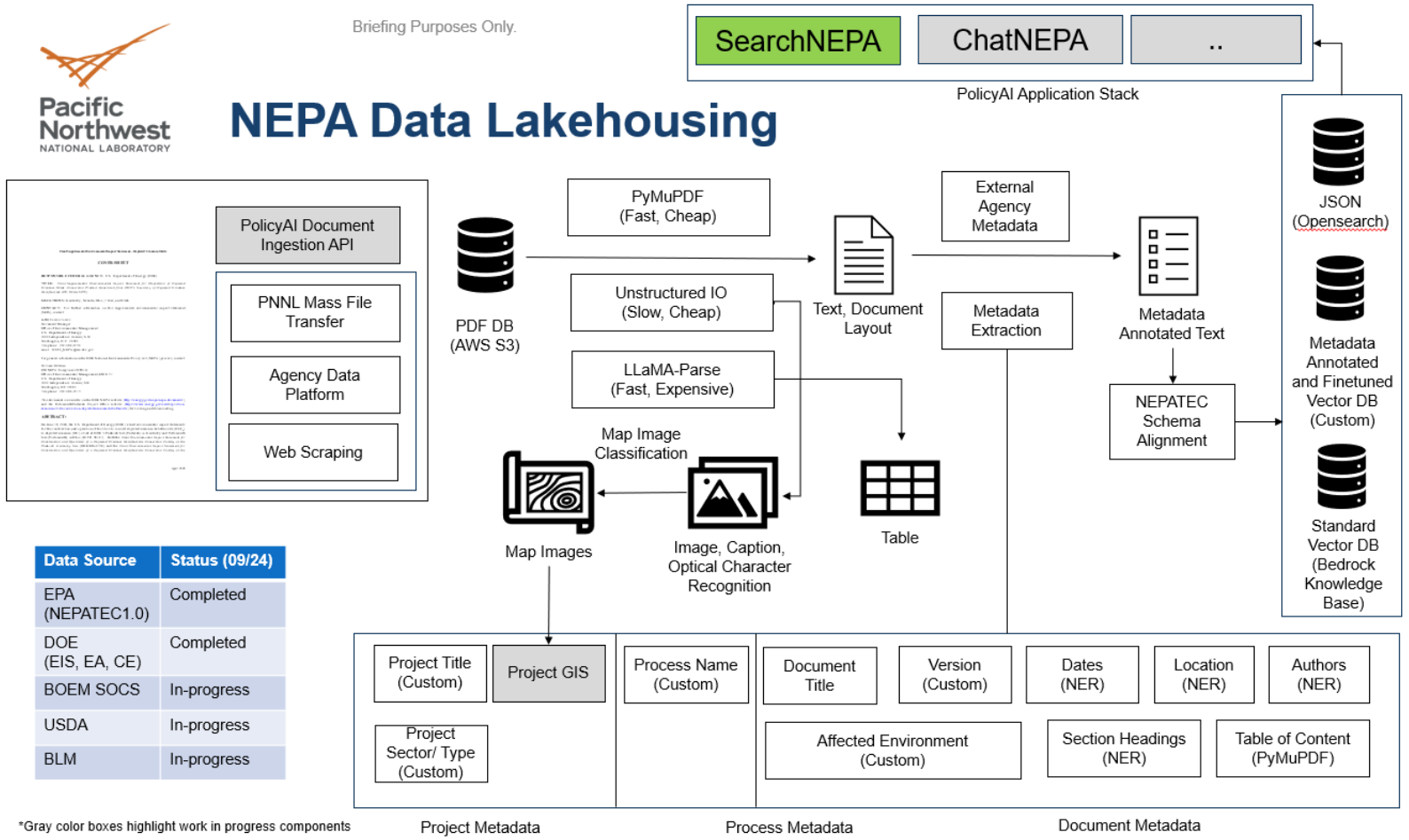
DOE's AI Governance team reviewed PolicyAI per M-24-10 and determined that PolicyAI is ***NOT*** rights-and-safety-impacting.

As new features are defined, the PolicyAI team will update reviews with DOE's AI Governance team and related OMB/GAO compliance.

Details on DOE's review of PolicyAI and compliance with federal standards

LESSON #1: THREE WORDS – DATA, DATA, DATA

- Absolutely necessary to spend substantial effort processing past data, adding metadata and other structure to the unstructured data.
- LLMs have proven effective as a tool for processing and producing better quality data, which will improve AI performance.



Data Source	Status (09/24)
EPA (NEPATEC1.0)	Completed
DOE (EIS, EA, CE)	Completed
BOEM SOCS	In-progress
USDA	In-progress
BLM	In-progress

*Gray color boxes highlight work in progress components

USING AI TO CREATE MORE STRUCTURED INFORMATION ON NEPA DOCUMENTS

Pacific Northwest NATIONAL LABORATORY

Database Schema

- Id: unique identifier
- Type: {EIS, CX, EA, OTHER}
- Published Date:
- Agency: DOE, DOD, etc.
- Cooperative Agency:
- Office:
- Project
  - Name:
  - Type: land management plan, discrete site construction project, linear project (pipeline, road, transmission line, etc.), regulatory change, etc.
  - Location:
- Title

Document Data Extraction

- FullText
  - Page Number:
  - Text
- Images: unique identifier for each images in the doc

Document Enrichment

- Purpose and Need/Proposed Action Description
- Affected Environment – Baseline conditions
  - Land Use/Visual/Transportation
  - Geology/Soils
  - Hydrology (groundwater/surface water)
  - Ecology (terrestrial/aquatic)
  - Air Quality/Meteorology/Climate Change
  - Historic & Cultural Resources
  - Human Health/Noise
  - Socioeconomics
  - Environmental Justice
  - Waste
  - Project Specific Hazards
- Resource impact assessments from construction and operation
- Cumulative impacts from other actions
- Alternatives to the proposed action and environmental impacts
- Mitigations/Conclusions

Briefing Purposes Only.

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Council on Environmental Quality
Report to Congress on the Potential for Online and Digital Technologies to Address Delays in Reviews and Improve Public Accessibility and Transparency under 42 U.S.C. 4332(2)(C)

Delivered to Congress, as directed in Section 110 of the National Environmental Policy Act of 1969, as amended.

"CEQ recommends defining data standards for agency or other applications, including a data architecture for the NEPA process and metadata for structured and unstructured data. These data standards could include an overall set of terms, definitions, and relationships in processes—called a taxonomy—for the NEPA process. The standards could also include specific metadata requirements for unstructured data, such as documents, structured data, such as tables or GIS data, and outcome-based metrics, such as key performance indicators that can optimize the process and improve efficiency and effectiveness."

USING AI TO CREATE MORE STRUCTURED INFORMATION ON NEPA DOCUMENTS

Pacific Northwest NATIONAL LABORATORY

LLM Generated EIS Standardized Structure

I. Front Matter

- Executive Summary
- Table of Contents
- List of Figures and Tables
- Acronyms and Abbreviations

II. Introduction

- Purpose and Need
- Project Description
- Alternatives

III. Affected Environment

- Soils and Geology
- Water Resources
- Wetlands
- Vegetation
- Wildlife
- Special Status Species
- Cultural Resources
- Visual Resources
- Recreation and Tourism
- Health and Safety
- Climate Change
- Noise

III. Affected Environment

- Soils and Geology
- Water Resources
- Wetlands
- Vegetation
- Wildlife
- Special Status Species
- Cultural Resources
- Visual Resources
- Recreation and Tourism
- Health and Safety
- Climate Change
- Noise

IV. Environmental Consequences

- Soils and Geology
- Water Resources
- Wetlands
- Vegetation
- Wildlife
- Special Status Species
- Cultural Resources
- Visual Resources
- Recreation and Tourism
- Health and Safety
- Climate Change
- Noise

V. Cumulative Impacts

- General
- Future Renewable Energy Projects

VI. Alternatives

- Alternative A
- Alternative Transmission Line Routes Eliminated from Further Study
- Central Route Alternative Considered but Eliminated from Analysis
- New Alternatives or Elements

VII. Consultation and Coordination

- General Comments
- Other NEPA Issues
- Draft Habitat Conservation Plan (HCP)
- Draft Restoration Management Plan (RMP)
- Draft Migratory Bird Conservation Plan (MBP)

VIII. References

IX. Appendices

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LESSON #2: GO SMALL OR GO HOME (SORT OF)

- Although models now have context windows with hundreds of thousands of tokens (or more) using the maximum context windows did not improve (and even slightly degraded) performance
- Commercial frontier models don't "speak NEPA" very well – NEPA is a highly specialized applied science domain
- PNNL researchers have trained a NEPA-GPT based on 3 billion parameter open-source Phi architecture with promising early results
  - 5 billion tokens of high-quality data
  - Initial results are promising – in line with literature that small domain-specific models can achieve comparable or better performance with much larger models
- Optimizing performance balanced with cost will require choosing correct model for the job

RAG vs. Long Context: Examining Frontier Large Language Models for Environmental Review Document Comprehension

Hung Phan[♠]; Anurag Acharya[♣], Sarthak Chaturvedi[♣], Shivam Sharma[♣], Mike Parker[♣], Dan Nally[♣], Ali Jannesari[♠], Karl Pazdernik[♣], Mahantesh Halappanavar[♣], Sai Munikoti[♣], Sameera Horawalavithana[♣]
[♠]Iowa State University
[♣]Pacific Northwest National Laboratory

Context	None	PDF	RAG	Gold
GPT-4	67.00%	63.70%	74.36%	**76.60%**
Claude	64.53%	66.46%	75.16%	**76.84%**
Gemini	62.84%	65.90%	75.46%	**81.15%**
Mistral	64.95%	61.81%	72.88%	**75.34%**
Llama3.1	66.35%	59.52%	**74.01%**	72.73%

Table 2: Answer correctness of LLM responses on the NEPAQuAD benchmark across different context types. The best-performing setting for each model is shown in bold.

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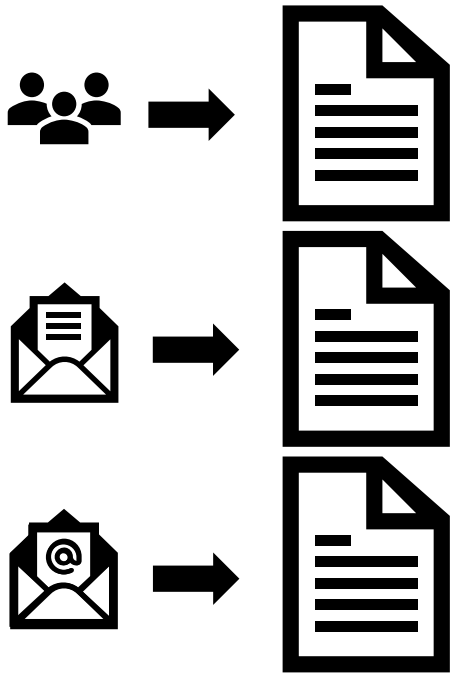
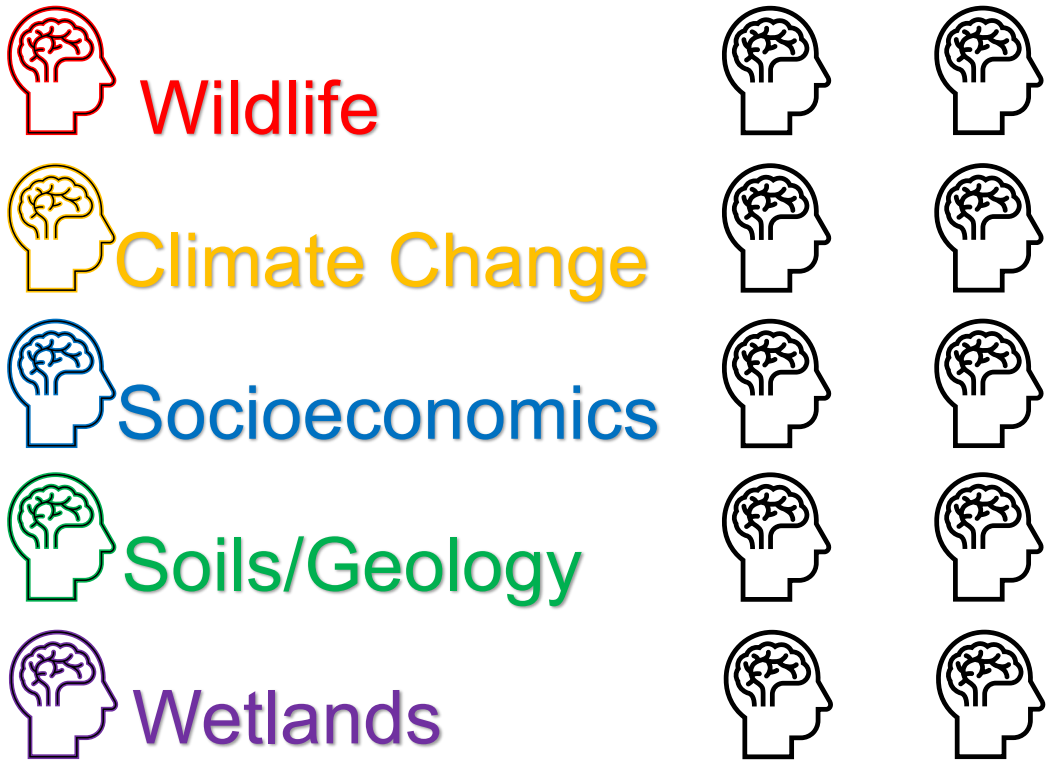
GOING SMALL - BREAKING DOWN THE WORKFLOW TO OPTIMIZE LLM PERFORMANCE





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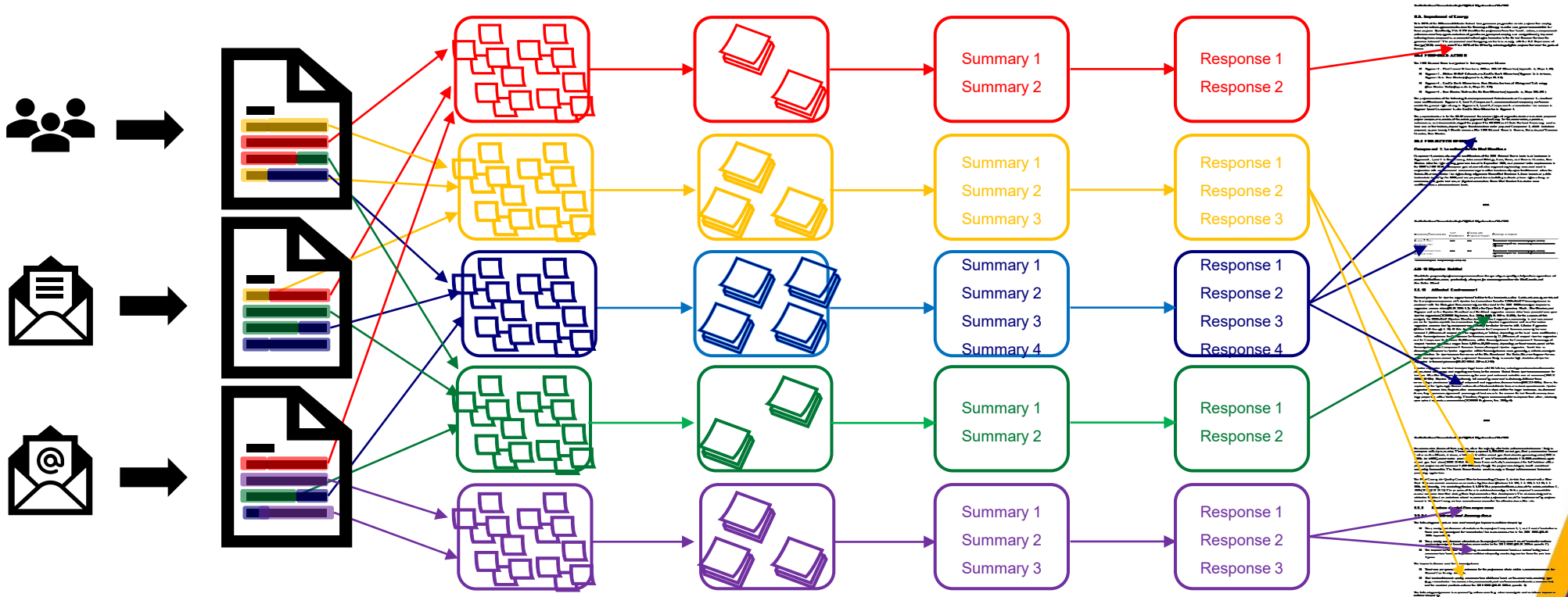

Submissions → AI Extracts MetaData & Categorizes Comments by SME Topic → AI Automatically Distributes Comments to SME's → AI/SME Groups Comments by Topic & Corrects Binning Errors → AI/SME Summarizes Comment Topics → SME Drafts Responses → SME makes revisions in EIS

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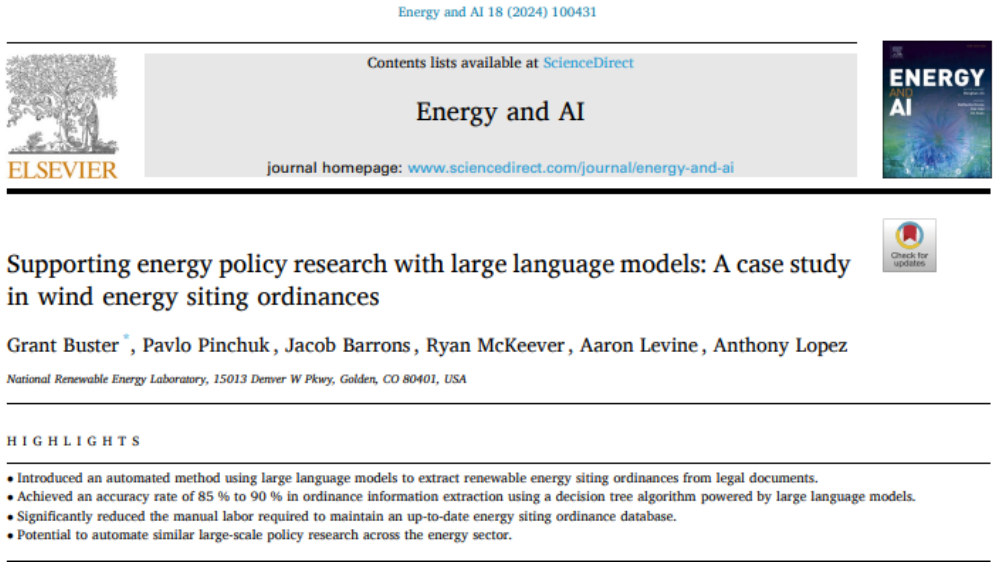
LESSON #3: BYOL – BRING YOUR OWN LOGIC

- Variety of systematic workflows can be developed to address shortcomings of LLMs
- NREL researchers utilized SME expertise, decision trees, and symbolic logic to have LLM extract quantitative information hundreds wind ordinances
- Accuracy comparable to past manual reviews, including on quantitative comparisons



Energy and AI 18 (2024) 100431

Contents lists available at ScienceDirect

Energy and AI

journal homepage: www.sciencedirect.com/journal/energy-and-ai

ELSEVIER

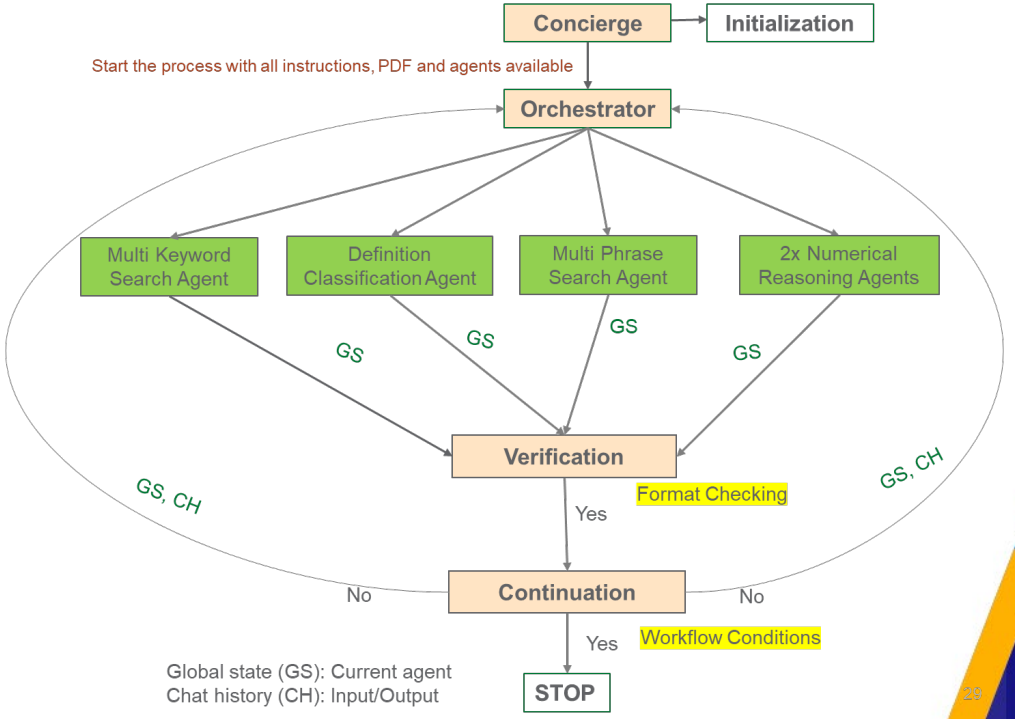
Supporting energy policy research with large language models: A case study in wind energy siting ordinances

Grant Buster *, Pavlo Pinchuk, Jacob Barrons, Ryan McKeever, Aaron Levine, Anthony Lopez

National Renewable Energy Laboratory, 15013 Denver W Pkwy, Golden, CO 80401, USA

HIGHLIGHTS

- Introduced an automated method using large language models to extract renewable energy siting ordinances from legal documents.
- Achieved an accuracy rate of 85 % to 90 % in ordinance information extraction using a decision tree algorithm powered by large language models.
- Significantly reduced the manual labor required to maintain an up-to-date energy siting ordinance database.
- Potential to automate similar large-scale policy research across the energy sector.



- PNNL Researchers tackling a similar problem with workflow using multiple language agents
- Goal is to first build the workflow following the exact instructions the human reviewers followed, then optimize for human/AI interaction

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POLICY AI – SearchNEPA

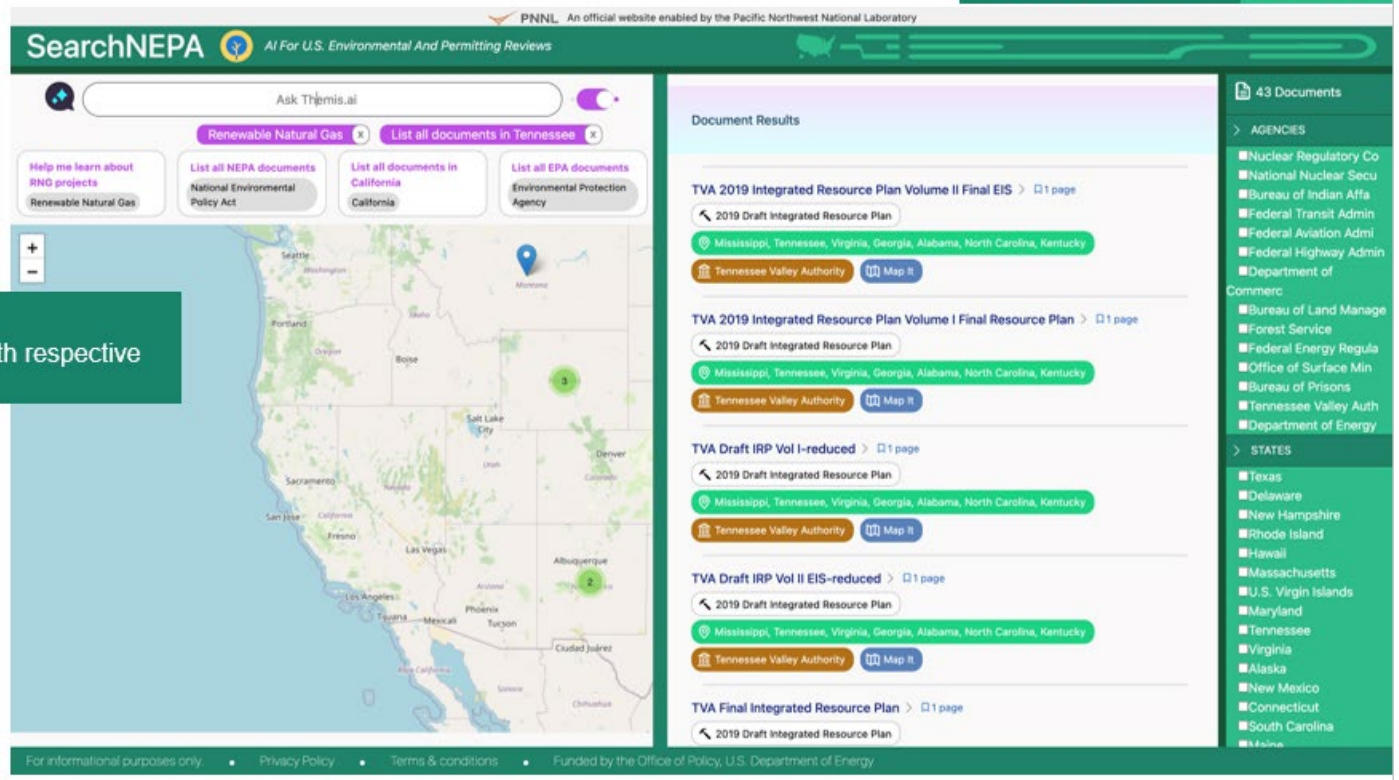
Pacific Northwest NATIONAL LABORATORY

SearchNEPA

Standard Document Full Text Search

https://policyai.pnnl.gov/searchnepa/

GenAI Search | Version 1.0



Features

- Prompt GenAI Search with respective Document Results

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POLICY AI – MULTIDOCUMENT SUMMARY

PolicyAI NEPA Search V0.01

proximate cause ✕ Press enter to add more

Proximate Cause in Environmental Impact Statements

Proximate cause within environmental impact statements (EIS) is primarily mentioned as the immediate or direct cause of an environmental impact or wildlife mortality. In legal and regulatory contexts, it refers to the primary action leading to an observed outcome. Here's a summary focused on **proximate cause**:

1. **Cumulative Impacts and NEPA**: Under NEPA, only impacts with a "reasonably close causal relationship" to the proposed action must be analyzed, akin to **proximate cause** in tort law. The Uinta Basin Railway EIS clarified that the project was not the **proximate cause** of regional oil and gas development as such activities could occur without the rail line [1].

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Document Status: Final

EPA Comment Letter Date: None

Federal Register Date: 08/06/2021

8. **Timber Operations and Environmental Compliance**: **Proximate cause** is vital in issuing stop orders for timber operations that are the direct cause of environmental violations or are forecasted to be the future **proximate cause** [11,12].
9. **Conservation Plans and Population Declines**: Poor ocean conditions have been identified as the **proximate cause** of declines in salmonid populations, emphasizing the importance of environmental factors in aquatic species conservation [13].
10. **Predator Management and Ungulate Populations**: Discussions in predator management EIS documents often make a distinction between **proximate** and ultimate causes of mortality, with predation being a significant proximate cause but influenced by ultimate causes like nutrition or habitat conditions [14].
12. **Quarrying Activities and Wildlife Mortality**: The Omya Sentinel & Butterfield Quarries Expansion EIS identified predation and ingestion of foreign materials as **proximate causes** of bighorn sheep mortality [8,16].

Bibliography:

1. **Uinta Basin Railway (Final)**, Surface Transportation Board pdf link
2. **National Petroleum Reserve - Alaska (NPR-A) Integrated Activity Plan (Final)**, Bureau of Land Management pdf link
3. **Casa Diablo IV Geothermal Development Project (Final)**, Bureau of Land Management pdf link
5. **Mitsubishi Cement Corporation South Quarry Plan of Operation (Final)**, Forest Service pdf link
6. **Multi-Project for Hydropower Licenses -Susquehanna River Hydroelectric Projects (Final)**, Federal Energy Regulatory Commission pdf link
7. **ADOPTION-Wilton Rancheria (Final)**, National Indian Gaming Commission pdf link
8. **Omya Sentinel & Butterfield Quarries Expansion (Final)**, Forest Service pdf link
9. **BP Cherry Point Dock (Final)**, U.S. Army Corps of Engineers pdf link

See Document

Thank You – Questions?