Why AI is not the “new electricity”

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What was “electricity” and what might the new “electricity” look like?

Electricity is a form of energy due to the existence of charged particles.

**Electricity-based advancement:** in some sense—the “Cronon” sense—our ability to expend more energy faster to do the same task or a new task — e.g., car vs walking or computer vs pen and paper calculation. (highly related to the second law of thermodynamics)

in this sense, figuring out how to **EXPLOIT ELECTRICITY WAS A REVOLUTION**
Impact of electricity

**Scale:** all manufacturing, computation, most medical care, home-life (cooking), travel, communication, etc., etc., *nearly all aspects of life are made possible or done much faster using electricity.*

**Universality:** electricity is the *underlying power* that we can spend *increasingly quickly*, enabling us to do nearly everything we do... *it is a power source that is spent.*

For something to be ”like electricity” it would have to act at the underlying power source that can be expended quickly and it must transform our society on the same *scale* as our exploitation of electricity — *nearly every task we undertake would have to be fundamentally impossible without it.*
AI as “electricity”

At its core AI makes predictions and we use these prediction to make a—broadly defined—decision or gain understanding, or—with control theory—automate a task.

AI—which costs and uses electricity—really facilitates our ability to use power but *it is not a source and it is not used everywhere.*

Aside: there are human limits to how much ”AI” we can spend to make a decision or have a decision made for us.
at an even more basic level...

the allegorical meaning of the words “AI is the new electricity” implies the question:

is AI the same revolution in the 21\textsuperscript{st} century that electricity was in the 20\textsuperscript{th}?

If AI was actually intelligent in a human sense ... then maybe the answer might be yes...
I would argue that...

**AI isn’t the new electricity, it isn’t even ”I”!!!**

AI is pitched using works like ”learn” and ”knowledge” in reference to what the machinery does—the machine “thinks”... the machine “knows”... the machine “learns”—but these words are very deceiving.

*What is intelligence?*

**Intelligence concepts that have eluded mathematization:** long-term memory, single instance learning, etc.
I would further argue that...

Electricity is the wrong analogy: AI isn’t a revolution, is a tool guiding:

- accurate, data-driven decisions;
- data-driven synthesis and understanding when we are overwhelmed with data and complexity.
Where my opinions come from: looking under the hood of AI/ML/etc.

AI is, in a broad sense, a regression... meaning:

it is a projection of data onto a function space, where the regression selects the function that most likely/accurately/etc. represents the data; the function selection is carried out via a minimization and is defined by estimates of function-specifying parameters that minimize a cost.

This may sound like *gibberish***!!!*, so let’s unpack it in the biomedical context...
Anchoring AI to a context: prediction and personalization in medicine

*Medical practice is about prediction*

When managing health, clinicians and hopefully people in general intervene in ways predicted to help more than hurt — clinicians generally weigh the consequences of probability of helping against hurting conditioned on the consequences of interventions.

Predictions are generally based on a model and data; but what constitutes a model can be very broadly defined.
Predictions clinicians can make are generally limited to what can be done **by hand or in their heads**.

Most of the details within the data are left behind... as are most complex relationships between the data.

This is how AI/ML/DA/etc. can help, but this is far different in allegory and function than *electricity*.

**The problem:** the conception of what AI/ML *are* and *can do*. 
Personalized prediction in a medical context: 5 elements

Prediction in a medical setting has five elements:

1. Data — the coal;
2. Models — first half of the power plant;
3. Inference machinery used to select the best model of the data — second half of the power plant;
4. Knowledge/forecast delivery methodology — power grid;
5. Context within the clinical setting and workflow — devices that use electricity.

And these elements exist within the overall context of clinical decision-making and understanding... and today we will only discuss items 2 + 3.
Models: modeling clinical data, the first half of the ML/AI or knowledge generation and synthesis

Data contain relationships between measurements and:

- other features/variables/measurements;
- outcomes;
- documentation behaviors...

and we represent these relationships with models/functions...

Machinery for representing of data with models/functions has two primary components:

1. the model/function space from which we select a model to represent data;
2. the inference machinery used to estimate (pick!) the model, or synchronize the model to data.
Model/function spaces come in three flavors:

1. parametric functions/models;
2. non-parametric functions/models;
3. parameterized-knowledge-driven functions/models.
But first... a regression cartoon
Parametric models or function spaces

Some examples:

1. Linear functions — two parameters used to represent the data, a mean (slope) and an intercept.

2. Gaussian distribution — two parameters to represent the data a mean and a variance.

Note: parametric means that the model is completely defined/specified by a fixed set of parameters, e.g., (mean, variance).

These models:

▶ have limited flexibility — these functions often cannot estimate data or a system very well...

▶ are easy to understand/interpret;

▶ require very little data to estimate/pick.
Non-parametric models or function spaces

Some examples:

1. polynomials \( \left( \sum_{i=1}^{N} a_i x^i \right) \);
2. artificial neural networks — i.e., deep learning;
3. Gaussian process models;

*Universal function spaces*, meaning there are theorems that state:

given enough terms/units these functions can approximate almost any function to any degree of accuracy desired.

Equivalency: these spaces or methods are *theoretically equivalent*—they differ only in their explicit representation of the data—their functional form (explicit equation)—and the methods used to pick which collection of functions *best represents the data*.

These models:

- have **infinite flexibility** — these functions—provably—are capable of estimate data or a system perfectly;
- are **difficult to understand/interpret**;
- require **tremendous amounts of data and energy** to estimate/pick;
- are generally harder to estimate/pick;
- the selection is not particularly unique or important — imagine selecting the type of grapes you want it eat if you have 100M choices.

...infinite flexibility comes with a cost....
Parameterized-knowledge-driven models or function spaces

Mathematical models of mechanistic physiology — they represent the *mathematization of our knowledge of the underlying system*

An example: the **Hodgkin-Huxley** model of neurons.

These models are:
- more complex than, but neither a sub- nor super-set of the generic parameterized families—e.g., linear functions.
- less complex than, **but are a subset of**, the non-parametric functions.

A way to think of these models in the broader vision:

*the model narrows the search space over the space of all functions according to our knowledge of physiology.*

These models:
- have **limited flexibility** — *these functions only estimate the system well if our knowledge of the system is correct!!!*
- are **easy to understand/interpret**;
- require **very little data** to estimate/pick.
DA uses a severely constrained — by our knowledge or hypotheses of how the physical system works — parameterized family of models, limiting the flexibility of what the model can do.

ML uses an unconstrained parametric or non-parametric family of models with almost no limits to what the model can do

Knowledge-based constraints have consequences:
But in end... these are all regressions — methods for selecting a function to represent the data from some set of functions!!!

And this is why AI is not:

- the new electricity;
- a revolution;

AI/ML/DA doesn’t think or learn or solve problems, it isn’t magic, etc....

AI just estimates models with data, and models are not and do not represent intelligence!
As a revolution...

It is unlikely that somehow we will just magically find the universal magic function space and inference scheme and optimization metric(s) that allow the machines will suddenly become intelligent, solve all our problems, allow us to never have to think again, making our lives “easy...”

What is missing for AI to be the new electricity:

1. scale!
2. universality!

AI is a facilitator a tool to help spend energy faster, for making better decisions, facilitating understanding, automating some tasks, and it isn’t a raw material with universality and scale like electricity is.

electricity is still the “new electricity”
Asking AI to be electricity is asking too much and making the wrong request

While AI/ML/DA etc. are often pitched with words we use to describe human intelligence, **AI methods are not related to intelligence literally or metaphorically!**

Fundamentally, AI and all data science methods essentially the same, they are defined using:

\[ \text{model} + \text{cost function} + \text{inference/minimization} \]

and these are not magical black boxes that can do anything nor are they intelligent.

**BUT** that is all OK! AI is still **SUPER** useful!
but!!! AI/ML/DA and data analytics are still very valuable!

AI/ML/DA/etc. compute and synthesize data that allow us to:

▶ Synthesize data and help create new knowledge;
▶ Understand complex, nonlinear systems;
▶ Reduce and synthesize incomprehensibly large data sources to digestible forms;
▶ *Help humans make better decisions!!!! and decisions we would otherwise not be able to make!!!*
▶ Automate simple repetitive decisions that require minimal human insight and automatically run many rudimentary tasks, etc.;
▶ Personalize medicine by solving the ”compute in your head” problem;
▶ Make the processes more efficient and/or fast.

so AL/ML/DA are very helpful, and can potentially be transformative, but they are not the “new electricity”

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boo!

really! BOO!
The plumbing-schematic for personalizing medicine

**Data sources:**
- EHR/Clinical data
- Outside Knowledge (literature, etc.)
- Omics (genetics, etc.)
- Devices/Monitors/Cyborg-Robotics/Implanted-Monitors/Wearables/External-Monitor
- Basic Science

**Data translation:**
- Data munging of EHR data
- Translation of information/knowledge into computable forms
- Pre-processing of monitor data

**Knowledge creation --- Data analysis/analytics:**
- Machine Learning, AI, Data Assimilation, Generally Data Science, ETC.

**Knowledge translation:**
- Human-Computer-Interaction
- Human Factors
- Interface design

**Deployment for decision-making:**
- Clinician use, deployment, evaluation, etc.
- Self-management deployment, use, evaluation
- Policy-level use

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Related papers:

1. "Mechanistic Machine Learning: how data assimilation leverages physiologic knowledge using Bayesian inference to forecast the future, the infer present, and phenotype." with BG, GH, ML, LM, and AS in JAMIA.


4. ”High fidelity phenotyping,” GH and DA in JAMIA.


10. “Using time-delayed mutual information to discover and interpret temporal correlation structure in complex populations,” with GH, CHAOS.


12. “Next-generation phenotyping of electronic health records” with GH, JAMIA;

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