THE FUTURE OF AUTOMATED HEALTHCARE

Frank Rudzicz
THE PRESENT OF AUTOMATED NEWS

- 61% of millennials get their news from Facebook (Pew Research).
- Facebook wants to maximize your ‘engagement’ with its news posts.
  - “Engagement is good” – you get to interact with the news that matters to you (and Facebook can use your preferences to sell you to advertisers).
- Facebook’s AI algorithms sort potential news to show you; something like:

  \[
P(engagement|\text{relevance}) = \lambda_1 P(Like|\text{relevance}) + \lambda_2 P(comment|\text{relevance}) + \cdots
\]

- Machine learning optimizes weights \( \lambda_i \) and the probabilities themselves.
Facebook’s algorithms sort potential news to show you: something like:

- You’re more likely to Like something if:
  a) your like-minded friends like it, too,
  b) you agree with the content, politically (confirmation bias),
  c) …
- There’s a finger on the scale. A feedback loop.
• The risk is not disobedient artificial intelligence, but instead obedient artificial intelligence mixed with lazily-defined objectives.

• Social media shows us that simple algorithms designed for innocuous purposes can have disastrous unintended consequences, if mixed with hidden human biases.

“First we shape our tools, and thereafter our tools shape us.”

- Marshall McLuhan

• What simple algorithms are being designed in healthcare?
THE FUTURE OF AUTOMATED HEALTHCARE

• What are some **current trends** in AI for healthcare?

• What **technical risks** exist? How can we patch them?

• What **regulatory hurdles** exist? How can (should?) we surmount (circumvent?) them?
  - What changes are likely coming for our **society**?
CURRENT TRENDS IN MACHINE LEARNING
TRENDING NOW

1. Deep neural networks (of course)
2. Big Data (with cells interlinked within cells interlinked)
3. Recurrent neural networks for temporal, dynamic data
4. Reinforcement learning
5. Active learning
6. Telehealth and remote monitoring
7. Causal, explainable models
1. DEEPER, DEEPER STILL

It's a freaking cat.

‘hidden’ representations are learned here
1. DEEPER, DEEPER STILL

Trained with 129,450 clinical images
Tested against 21 certified dermatologists.

2. BIG (INTERLINKED) DATA

- Modern deep learning *usually* requires a **large amount** of data to work.
- Fortunately, when the data set is very big, the need to **preprocess** it decreases.
- Supervised training needs **labels**; often in healthcare the labels come from **validated assessments** recorded in parallel.
- Sometimes we use unsupervised training, e.g., cluster analysis.
- The real promise of Big Health Data is in the interconnections that exist **between** Big Data sets.
2. BIG (INTERLINKED) DATA

3. TIME SEQUENCES AND RECURRENT DYNAMICS

- Unfortunately, for very long sequences, this pseudo-Markov process quickly forgets earlier information.
- E.g., this network might have almost no idea what to predict after “I grew up in France so I’m pretty good at speaking ….”
3. TIME SEQUENCES AND RECURRENT DYNAMICS

Long short-term memory networks

Clockwork recurrent networks
3. Time Sequences and Recurrent Dynamics

- Long-term trends are observable over milliseconds and over years.

4. REINFORCEMENT LEARNING

• **Reinforcement learning** was inspired somewhat by behaviourist psychology.

• Systems learn ‘online’ in the real-world (theoretically) by taking imperfect observations, inferring the unseen state of the world, and then taking an action.

• Actions are chosen to maximize an expected reward, or to minimize an expected cost.

• These rewards and costs are usually supplied by humans.

• In order to learn, some exploration is necessary.
4. REINFORCEMENT LEARNING

Be careful about reward hacking!
4. REINFORCEMENT LEARNING

- Any interaction with a simulated human doctor will likely use reinforcement learning to choose what questions to ask, what labs to order, what interventions to prescribe...
  - Rewards and costs are usually supplied by humans.
  - In order to learn, some exploration is necessary.

5. **ACTIVE LEARNING**

Our Facebook scenario from before was basically a form of active learning.
6. READING YOUR MIND FROM KILOMETERS AWAY

• **Language** provides a detailed lens into human cognition and **sentiment**.

• Language decline is an early hallmark of Alzheimer’s.

• Specific brain regions serve specific linguistic functions.

• How to measure the linguistic symptoms of cognitive decline?
6. ASSESSING ALZHEIMER’S ON YOUR COUCH

- A **picture description** task can be done in less than a minute, on the couch.

- **DementiaBank:**
  - 240 samples from 167 people with AD,
  - 233 samples from 97 controls.
  - Free-form descriptions of “Cookie Theft” (incl. audio)
  - Transcribed and annotated, e.g., with filled pauses, paraphasias, and unintelligible words.

- **Mini-mental state exam (MMSE)**
6. ASSESSING ALZHEIMER’S ON YOUR COUCH

State-of-the-art accuracy: 85% - 92%

Lexical
- Frequency;
- Avg. word length;
- # demonstratives;
- Familiarity Honoré statistic

Syntactic
- Parse tree depth;
- VP → VPG;
- VP → AUX VP;
- Coordinate conjunctions;
- Mean clause length

Acoustic
- Phonation rate;
- Mean F2;
- Mean RPDE;
- Mean power;
- Pause::word ratio

WINTERLIGHT
winterlightlabs.com
6. NEUROPSYCHIATRY ON TWITTER

• Very similar approaches can be taken for neuro-psychiatric disorders such as depression, anxiety.

• Traditional bag-of-words approach used dictionaries of happy and sad words, simple counts, and regression.

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<tr>
<th>tweets</th>
<th>Hamilton Rating for Depression</th>
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<tbody>
<tr>
<td>best day of my life</td>
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<td>sunny and pleasant, despite some rain</td>
<td>8/50</td>
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<tr>
<td>I’m glad this stupid sunny day is over</td>
<td>19/50</td>
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6. NEUROPSYCHIATRY WITH SIRI

How to avoid this, or at least assign responsibility if when it happens?
7. CAUSAL, EXPLAINABLE MODELS

• Two criticisms of neural networks:
  
  • **Correlation is not causation.** Neural networks learn to associate input features with output categories, but there is no abstract logic or interpretable reasoning to those associations.
  
  • It is not logical to say a particular biomarker causes the system to identify a particular disease; certainly not for a new case.
  
  • **You can’t explain that.** Neural networks are just matrices of \( \mathbb{R} \) numbers. You can’t tell why or how a neural network made a decision; you can’t assign responsibility.
Think rationally
Act rationally
Think like a human
Act like a human

7. MAKING ALIEN MINDS

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Labels with >99% confidence