Thus Spoke the Dalek: Explain!
A Short Introduction to Explainable AI

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Most of the following is taken from joint work with:

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Explanation and Comprehensibility in AI and ML (the 1980s)
Comprehensibility of symbolic knowledge as one of the major distinctions between logic-based and statistical/neural approaches in computer science.

Michie’s criteria for Machine Learning (ML):

1. **Weak criterion:** ML occurs whenever a system generates an updated basis building on sample data for improving its performance on subsequent data.

2. **Strong criterion:** Weak criterion + ability of system to communicate internal updates in explicit symbolic form.

3. **Ultrastrong criterion:** Strong criterion + communication of updates must be operationally effective (i.e. user required to understand updates and consequences to be drawn from it).
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Most state of the art systems implement weak ML approaches. Deep Learning (seems to be) almost necessarily of the weak type: Representations are internally learned, resulting in problem of “symbol reference” for hypothetical symbolic output. Laudable exception(s): Some systems in the ILP/IFP/SRL space.
HOW A DEEP NEURAL NETWORK SEES

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A Very Quick ILP Primer

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Explainable AI
; grandparent without PI
p(X,Y) :- father(X,Z), father(Z,Y).
p(X,Y) :- father(X,Z), mother(Z,Y).
p(X,Y) :- mother(X,Z), mother(Z,Y).
p(X,Y) :- mother(X,Z), father(Z,Y).

; grandparent with PI
p(X,Y) :- p1(X,Z), p1(Z,Y).
p1(X,Y) :- father(X,Y).
p1(X,Y) :- mother(X,Y).

; greatgrandparent without PI
p(X,Y) :- father(X,U), father(U,Z), father(Z,Y).
p(X,Y) :- father(X,U), father(U,Z), mother(Z,Y).
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p1(X,Y) :- father(X,Y).
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; ancestor without PI
p(X,Y) :- father(X,Y).
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p(X,Y) :- mother(X,Z), p(Z,Y).

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p(X,Y) :- p1(X,Y).
p(X,Y) :- p1(X,Z), p(Z,Y).
p1(X,Y) :- father(X,Y).
p1(X,Y) :- mother(X,Y).

Figure: Prolog programs for grandparent/2, greatgrandparent/2, and ancestor/2 with and without PI (p1/2 equiv. parent).
Types of AI/ML Systems from Opaque to Comprehensible
Opaque Systems

- The mechanisms mapping inputs to outputs are invisible to the user.
- Can be seen as oracle making predictions over inputs, without indication of how and why.
- Examples:
  - Closed-source, proprietary AI.
  - Genuine “black-box approaches”: inspection of algorithm and implementation does not give insight into system’s reasoning.
Interpretable Systems

- User cannot only see, but also study and understand input/output mapping.
- Implies model transparency, requires some understanding of technical details of mapping.
- Examples:
  - Regression model (interpreted by comparing covariate weights to realize relative importance of features).
  - SVMs and linear classifiers (data classes defined by location relative to decision boundaries).
- Counterexample: Deep ANNs with automatically learned input features transformed through non-linearities.
Emits symbols along with its output (remember: Michie’s strong and ultra-strong machine learning), allowing user to relate properties of inputs to outputs.

User responsible for compiling and comprehending symbols, reasoning about them.

Comprehensibility is graded notion, degree of comprehensibility corresponding to relative ease/difficulty of compilation and comprehension.

Examples:
- (Some) ILP systems.
- Receptive field visualization on convolutional ANNs.
Figure: Notions of comprehension and interpretation are improvements over opaque systems, but remain distinct:
→ Interpretation requires transparency in underlying mechanisms.
→ Comprehensible systems are possibly opaque while emitting symbols usable for reasoning.
Towards patients, physicians should be like comprehensible models:
- Deliver diagnosis by explaining high-level indicators revealed in tests (i.e. system symbols).
- Not providing information about how medical tests and evaluations work.

Towards other doctors/medical staff, physicians may be like interpretable models:
- Sketch technical line of connecting patient symptoms and test results to particular diagnosis.
- Other doctors and staff can interpret diagnosis, ensuring that conclusions are supported by reasonable evaluation functions and weight values for presented evidence.
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Beyond the Status Quo: Explainable Systems
OED: A *statement or account that makes something clear; a reason or justification given for an action or belief*. 

Problem(s) for AI/ML:
- ML algorithms producing rules about data features to establish a classification decision (e.g., decision trees) shed light into *how*, not *why*, decisions are made.
- Visualizations/text provided along with a decision (e.g., in deep learning for CV) require human-driven post processing under their own line of reasoning.

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Explainable AI
Interpretable and comprehensible systems are lacking in ability to formulate **line of reasoning** explaining decision making process of model **using human-understandable features of input data**.

Interpretable and comprehensible models *enable* explanations of decisions, but do not yield explanations themselves!

**Reasoning** as critical step in formulating explanations about why or how some event occurred!
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Figure: Combine symbols emitted by comprehensible machine with (domain specific) knowledge base encoding relationships between concepts represented by symbols. Relationships between symbols in knowledge based can yield logical deduction about relationship to machine’s decision.
Figure: External system traits related to explainable AI. Traits depend not only on properties of learning machine, but also on users.
(Definitely Not) The End
Four general types of AI/ML systems:
- Opaque.
- Interpretable.
- Comprehensible.
- Explainable.

Interpretability and comprehensibility are different!
⇒ “White box” vs. “communicating black box”.

Both are lacking in ability to formulate line of reasoning explaining decision making process of model using human-understandable features of input data.

Explanation requires reasoning!