Recursive neural networks can learn logical semantics.
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Natural language inference
- Tree structured (recursive) NNs: Designed to compute vector representations for sentence meaning by semantic composition
- Can they really do this? Limited evidence or theory so far for robust functional composition
- We test this ability on artificial and natural data.
- Task: Natural language inference (aka textual entailment) James Byron Dean refused to move without blue jeans (entails, contradicts, neither) James Dean didn’t dance without pants

Learning relation composition
- You’ll never observe all word pairs – lexical relation composition fills in inevitable gaps in lexical knowledge for inference:
  \[
  \text{if} \{\text{animal \supset cat}, \text{cat \supset kitten}\} \rightarrow \text{animal \supset kitten} \\
  \text{if} \{\text{cat \equiv animal}, \text{animal \equiv non-animal}\} \rightarrow \text{cat \equiv non-animal}
  \]
- We use artificial data: ¬3k train pairs, 3k test over 80s.

TreeRNNs for natural language inference

Learning recursive, functional definitions
- Phrase and sentence meanings are built compositionally out of shorter phrases and sentences following a recursive structure.
- Testing ability to learn recursive structure: we train a model on short sentences and test it on longer ones.
- Data: Statements of propositional logic, 60k short training examples, 12k training examples of up to triple the length.
- NB: Model must compare statements with unvalued variables, more in common with 3-SAT than plain Boolean evaluation.

Monotonicity reasoning and quantifiers
- Monotonicity + quantification are a classic case study for formal semantics: If all dogs bark, do all animals make sounds?
- Artificial data with a 20 word vocabulary:

Can NNs learn to do inference over real English?
- Train/test on SICK entailments (4.5k training examples).
- Best purely-learned system to date, but even with words from GloVe, noisy extra data from DenotationGraph, and significant preprocessing, accuracy still below the SotA (77% vs. 85%).
- 4.5k examples is not enough to learn English compositional semantics. Need more data and better unsupervised methods.

Compositional neural model networks for natural language meaning already do well on phenomena like semantic similarity and sentiment that engage the strengths of these models’ continuous vector representations. Our artificial data experiments find no fundamental obstacles to also being able to learn representations capable of modeling formal semantic notions of meaning composition from scratch, given enough data.