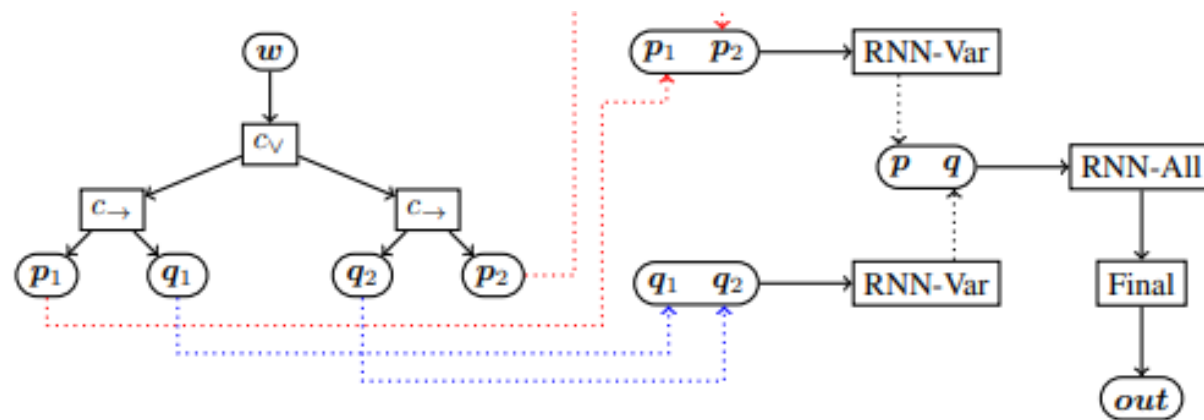


Directed Graph Networks

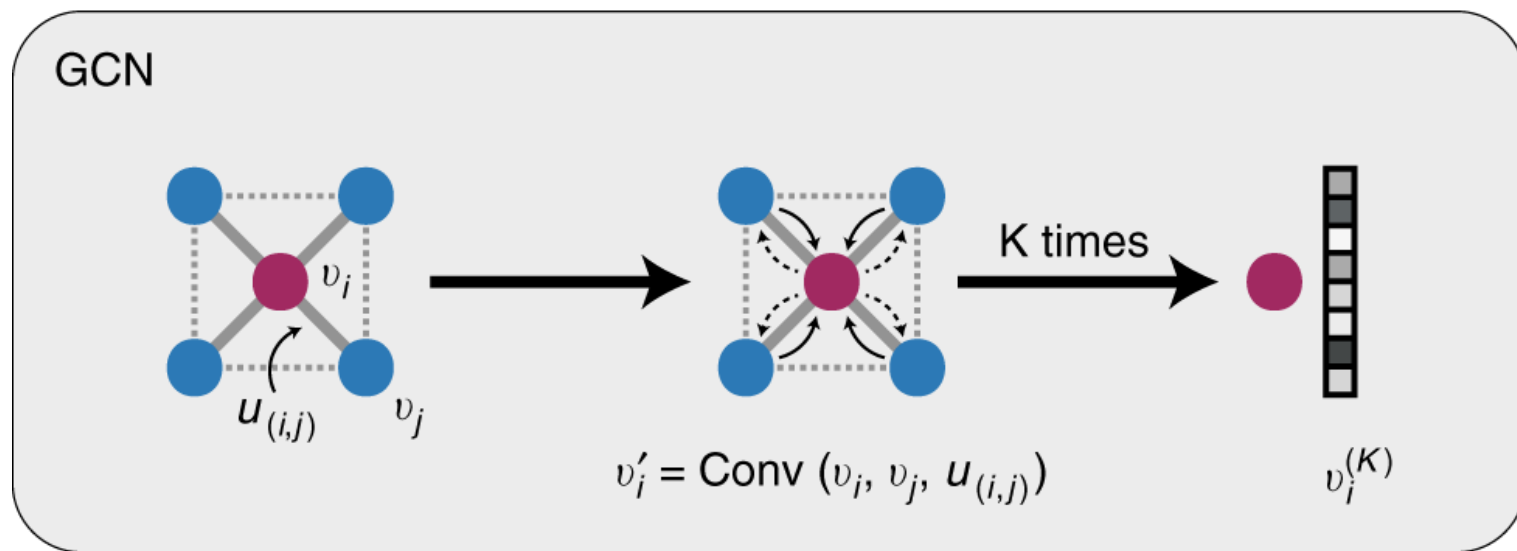
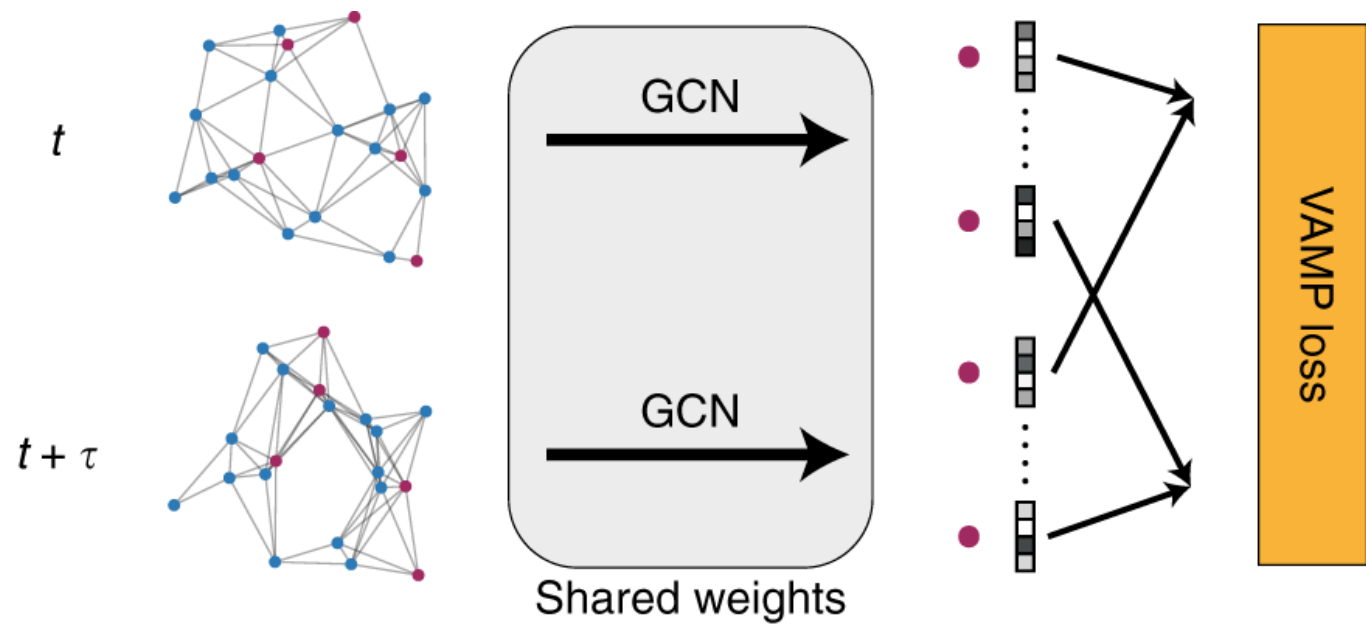
Neural Networks for Logic

- Sequence NNs: LSTM, 1-D convolutions
- Tree-like. TreeRNNs, TopDownNet
- Algorithmic assistance (cheating?): PossibleWorldNet
- (hyper-) graphs...



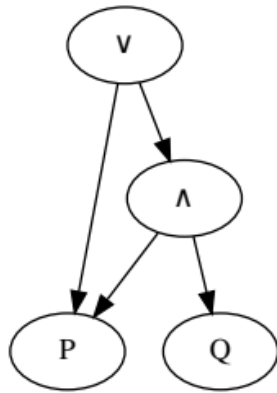
Graph Neural Networks

- Treat inputs as a graph (typically undirected)
- Each node has some feature vector attached: maybe edges as well
- Pass messages to neighbours to produce a new vector: “convolution”

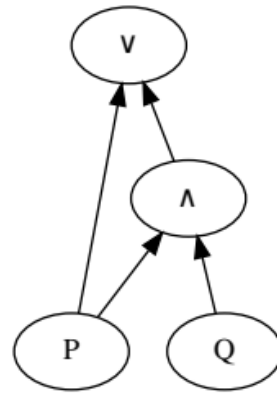


GNNs for logical formulae

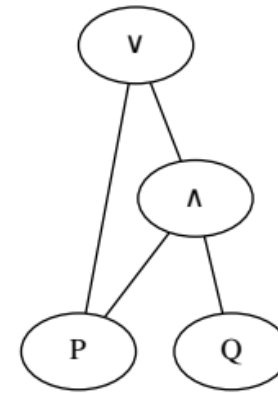
- Natural, avoid learning to parse structure
- Captures e.g. variable binding pleasantly, invariant (!) to e.g. associativity, alpha-equivalence
- Undirected graphs lose structure, directed graphs only pass messages one way?



(a) top-down only

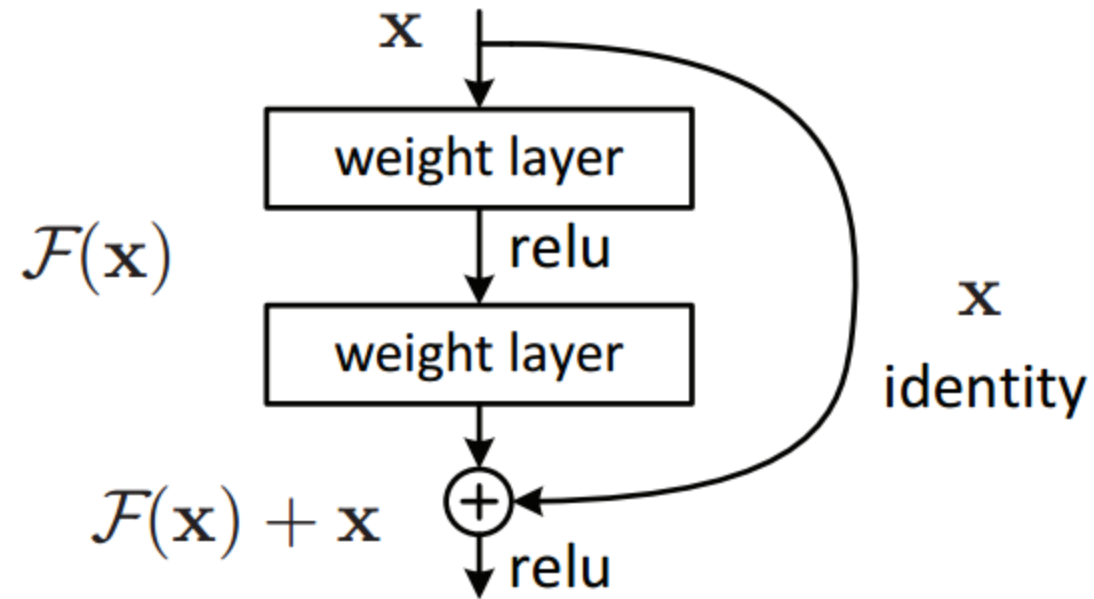


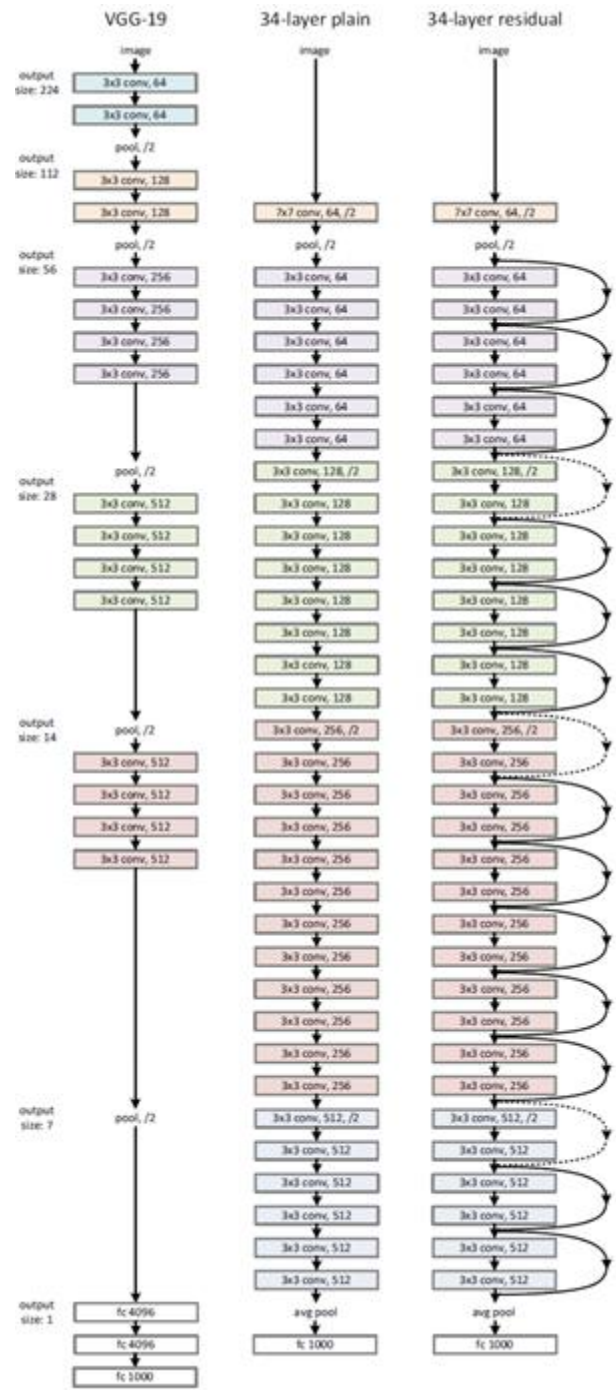
(b) bottom-up only



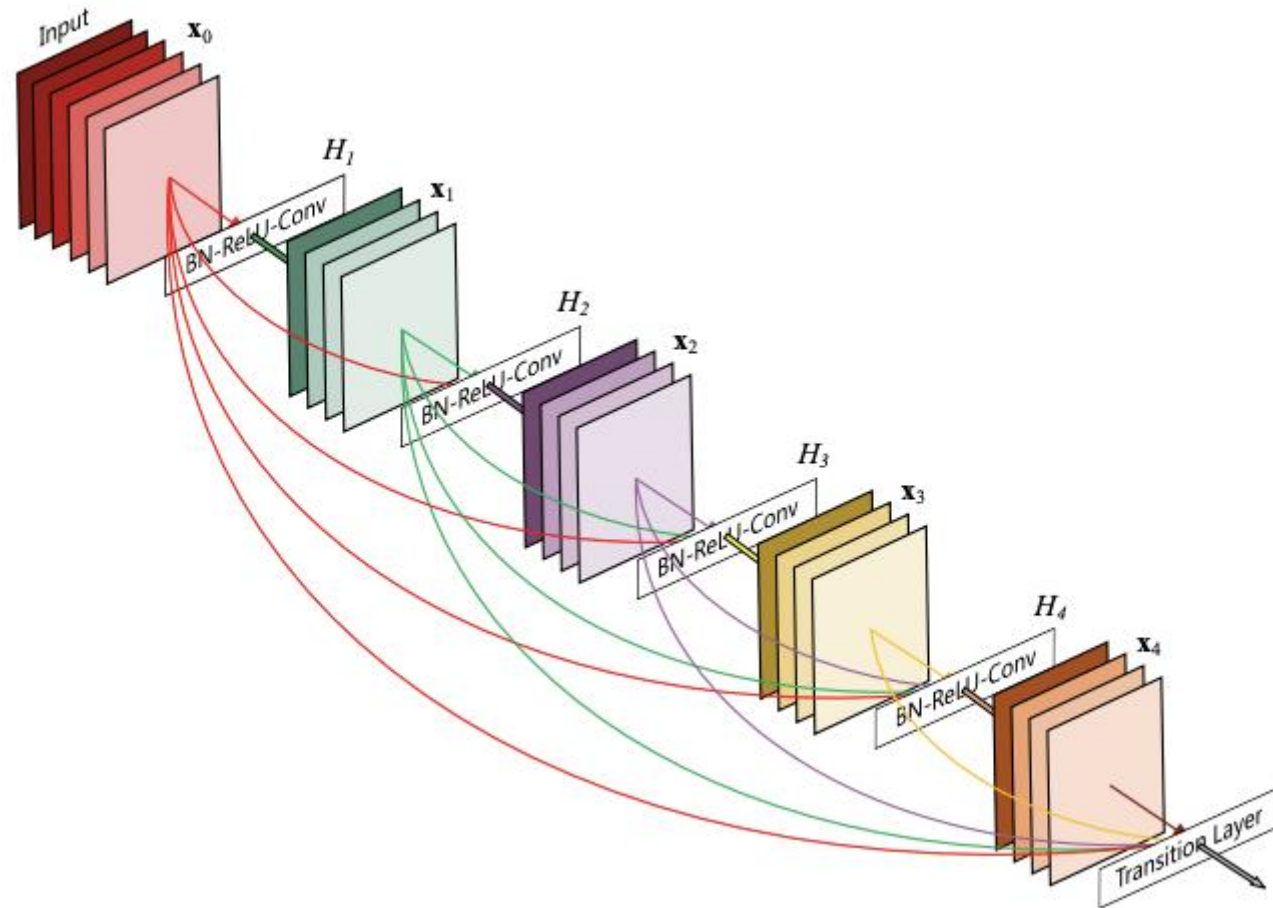
(c) undirected

Aside: residual networks





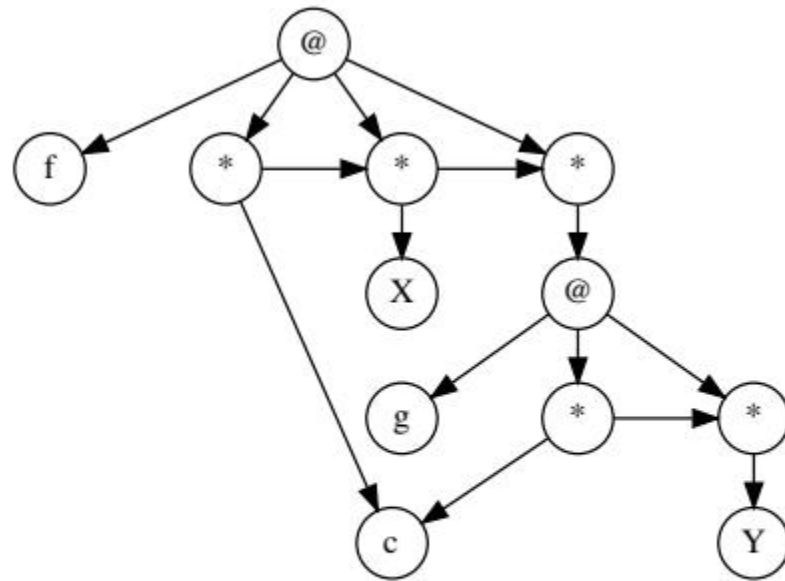
Dense Networks



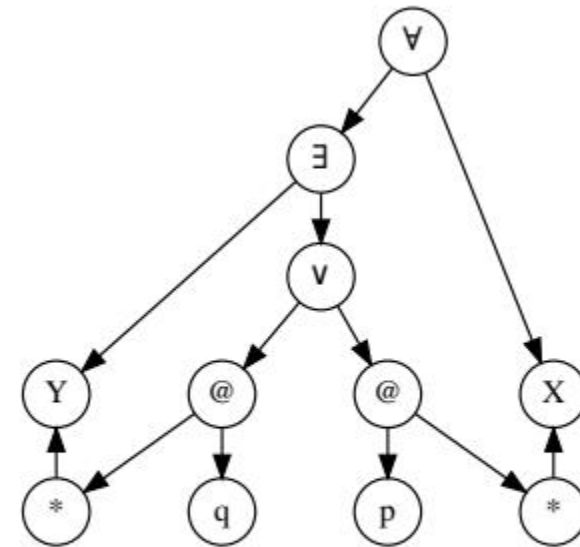
Bidirectional Graph Networks

- Idea: “convolve” in *both* edge directions
- Factor-2 blowup in feature size for each layer
- Use feature-reduction layers of e.g. *DenseNet* to control blowup

Directed Graphs for FOL



(a) $f(c, X, g(c, Y))$



(b) $\forall x. \exists y. P(x) \vee Q(y)$

Figure 3: First-order graph encodings, showing (a) argument ordering and (b) variable binding.

Tips & Tricks

- Cyclic learning rate really helpful for this
- Vanilla SGD+Nesterov momentum
- Batch normalisation: a bit unclear but theoretically good.

Results

- 79.8% DeepMath unseen set

Table 3: Propositional Entailment Accuracy

model	valid	easy	hard	big	massive	exam
PossibleWorldNet	98.7	98.6	96.7	93.9	73.4	96.0
TopDownNet	95.5	95.9	83.2	81.6	83.6	96.0
Contribution	99.4	99.3	91.2	88.3	89.2	97.0

The Future

- Pooling?
- Hypergraphs?
- Weird convolutions?
- New domains?