Neural Networks for Solving Truth Tables

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Background and Task

- Truth tables encode the value of a propositional formula as a function of the values of the formula's variables.
- Given formula *f*, each row of the truth table for *f* consists of an assignment *w* and the value of the interpretation function *I(f, w)*, which determines whether or not *w* satisfies *f*.
- **Goal:** learn *I(f, w)* to fill out truth tables for arbitrary formulae

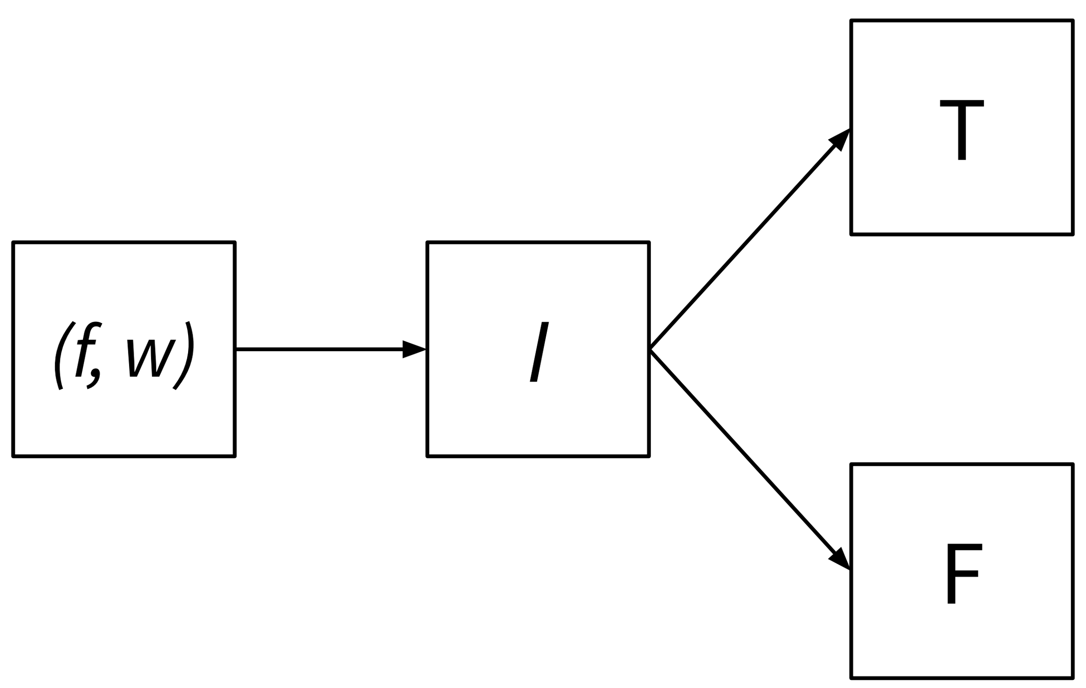

Fig. 1. Interpretation as a classification task on *(f, w)* points

p	q	p∨q
T	T	T
T	F	T
F	T	T
F	F	F

Fig. 2. An example of a truth table

Data

- Artificially generated formulas by randomly adding symbols/variables
- Labeled using oracle function that recursively evaluates formula
- For simplicity, all formulae had at most 3 variables
- Each test/train run uses newly generated random data

Formula	*P* and *Q*	*P* and *Q*		*R* and (not *S* or *T*)	*R* and (not *S* or *T*)	
Assignment	{*P*: 1, *Q*: 1}	{*P*: 1, *Q*: 0}	...	{*R*: 1, *S*: 1, *T*: 1}	{*R*: 1, *S*: 1, *T*: 0}	...
Label	1	0		1	0	

Fig. 3. An example of labeled data as *(f, w, I(f, w))* points

Implementation

- Neural networks have demonstrated incredible success in recent years on classification tasks
- Interpretation function is a classifier for formulas and weights
- Our featurization scheme allows us to create a fixed-length representation of formula *f* and assignment *w*

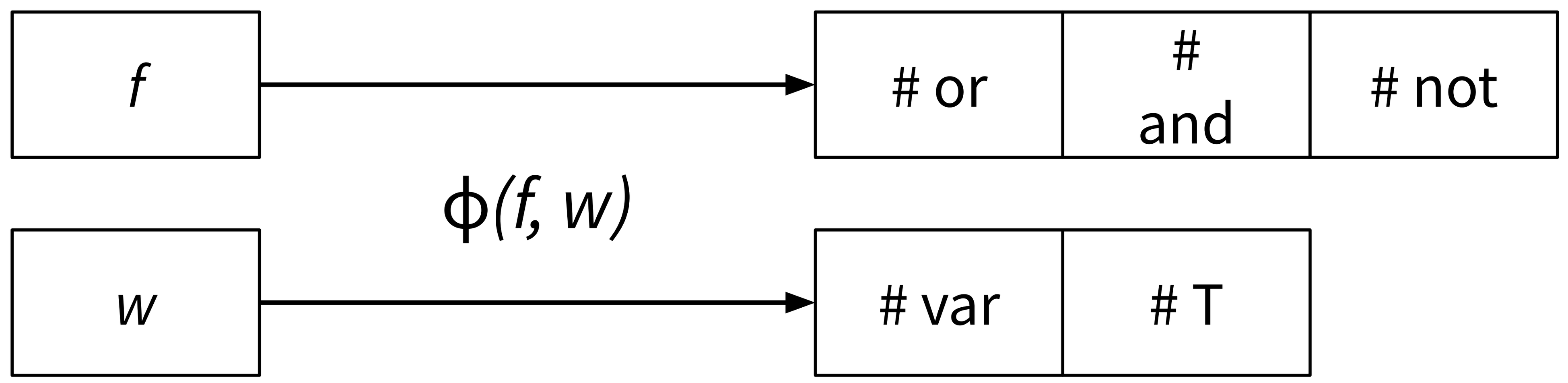

Fig. 4. Featurization of formula *f* and assignment *w*

Results

- Conducted a parameter sweep of all 3 layer networks with 2 to 10 units per layer
- Highest performing model used a (5, 4, 3) architecture, achieving an 87% accuracy

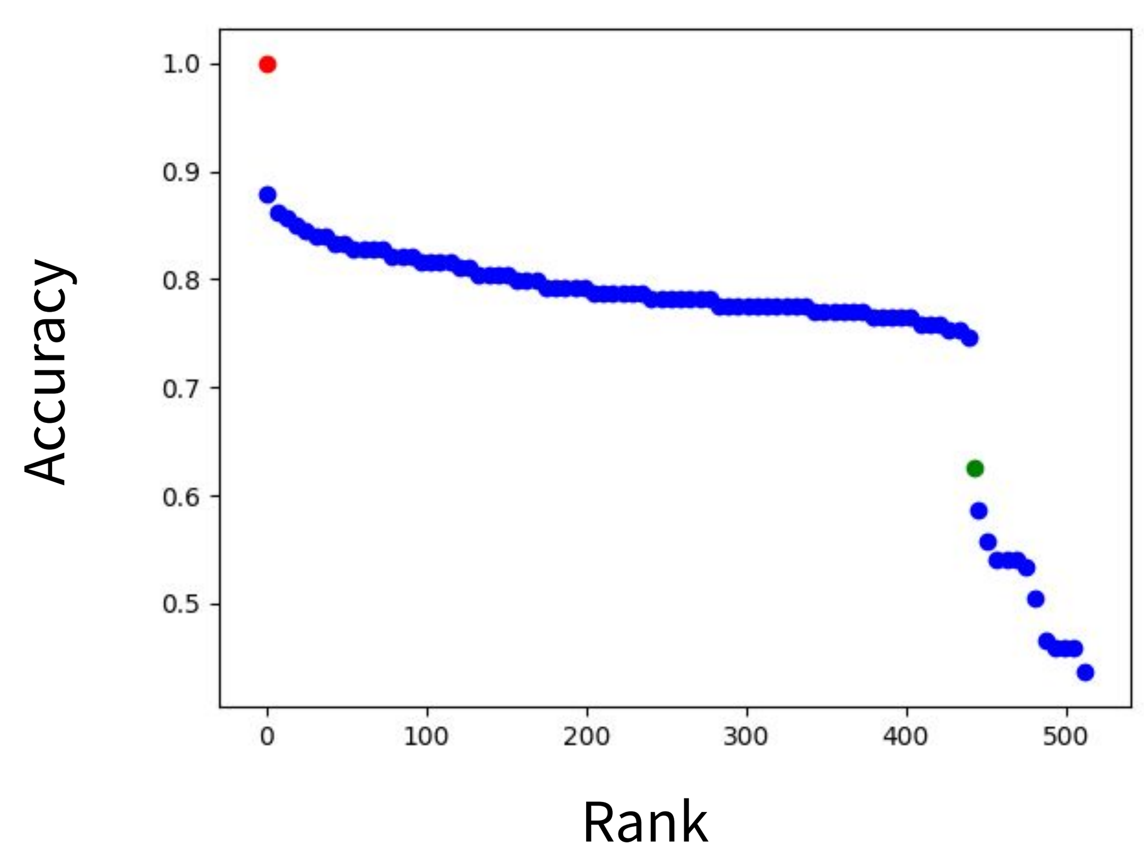

Fig. 5. Hyperparameter sweep, oracle in red, baseline in green, used to optimize architecture of neural network for classification

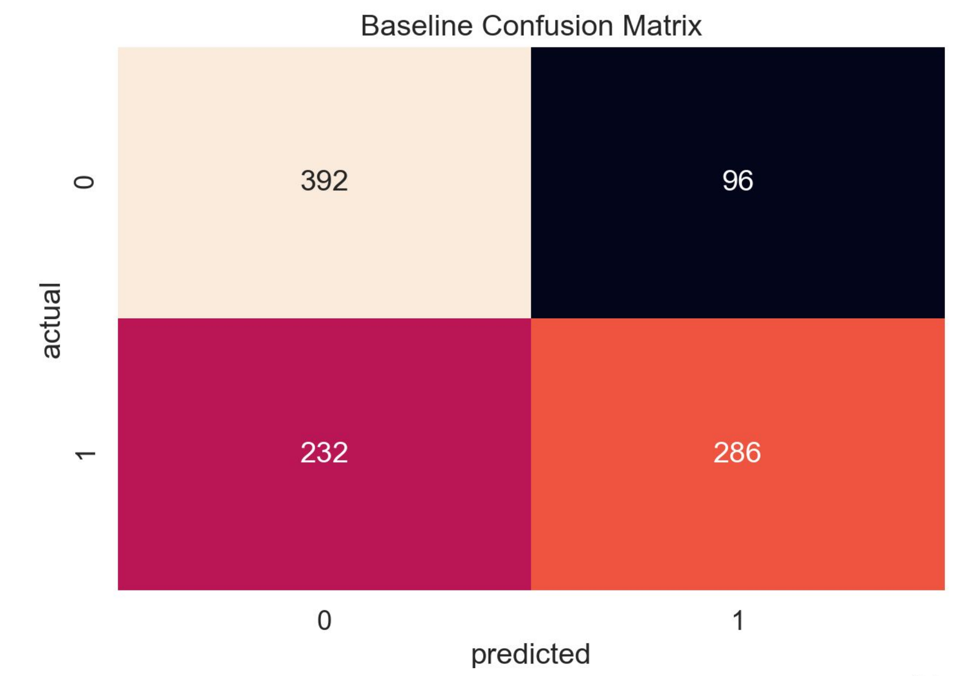

Fig. 6/7. Confusion matrices for each approach, demonstrates ability of neural net to better classify unsatisfied formulae