# Neuro-Symbolic Modeling: Overview

Some examples of neural-symbolic integration



### This lecture

- The Two Systems of Thinking
- Learning & Reasoning
- History: Statistical relation learning
- Some examples of neural-symbolic integration
- Technical challenges for neural-symbolic integration
- A taxonomy of approaches

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- 2. Semantic role labeling
- 3. Using the rules of a game to play the game

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Examples from the MNIST digit recognition dataset

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Given an image, recognize the digit in the image

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The label for the input  $\mathfrak{T}$  is 5  
Label( $\mathfrak{l}$ ) = 1



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Label(
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 $\downarrow$   
The label for the input  $\mathbf{5}$  is 5  
The label for the input  $\mathbf{1}$  is 1

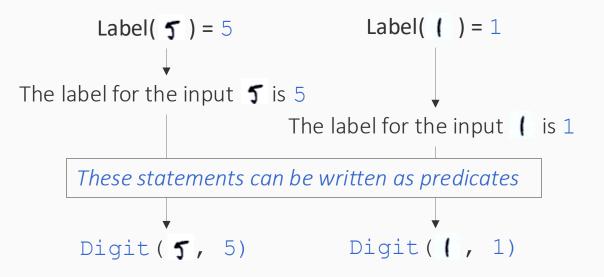


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As a predicate: Sum ( **5**, **1**, **6**)

"The model predicts a digit y for an input image x" = Digit (x, y)

We can imagine another model that predicts the sum of two digit images

Sum $( \mathbf{7}, \mathbf{1}) = 6$  The sum of these two digits is 6

As a predicate: Sum ( **5**, **1**, **6**)

"The model predicts a sum y for input images  $x_1, x_2$ " = Sum ( $x_1, x_2, y$ )

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Given data for one task and this rule, can we train a model for the other task?

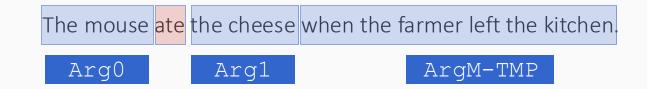
# Let's look at a few examples

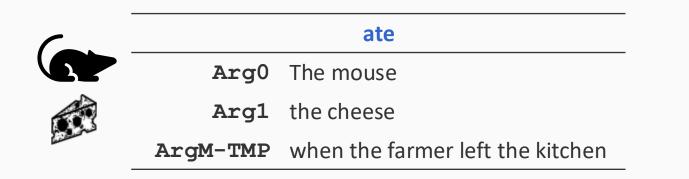
- 1. Recognizing digits and adding them
- 2. Semantic role labeling
- 3. Using the rules of a game to play the game

Who did what to whom, where, when, why?

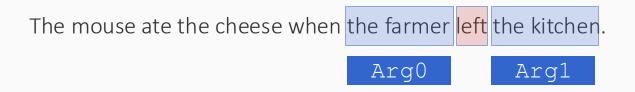
The mouse ate the cheese when the farmer left the kitchen.

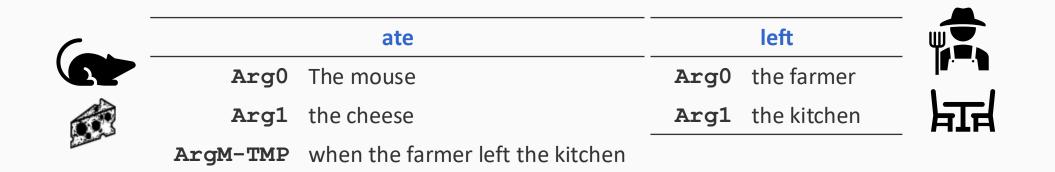
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These *semantic roles* are defined by the PropBank data (Palmer et al)

6	ate		left		
	Arg0	The mouse	Arg0	the farmer	-   <b>r1</b>
	Argl	the cheese	Argl	the kitchen	_ ਸਿਸ
and the second	ArgM-TMP	when the farmer left the kitchen			

#### What do the labels mean?

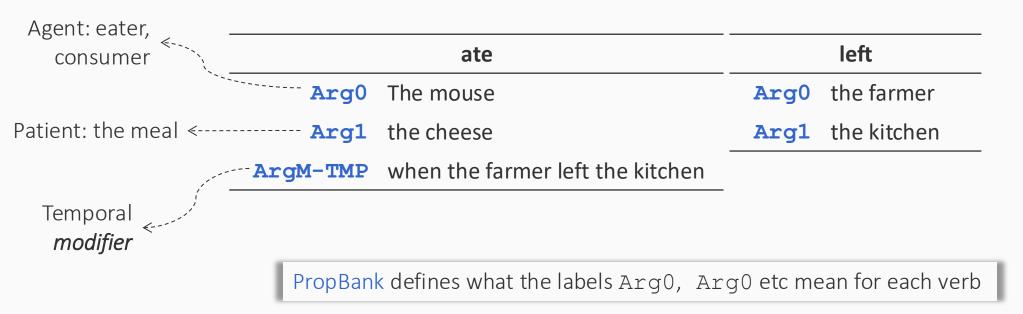
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ate			left		
Arg0	The mouse	Arg0	the farmer		
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PropBank defines what the labels Arg0, Arg0 etc mean for each verb

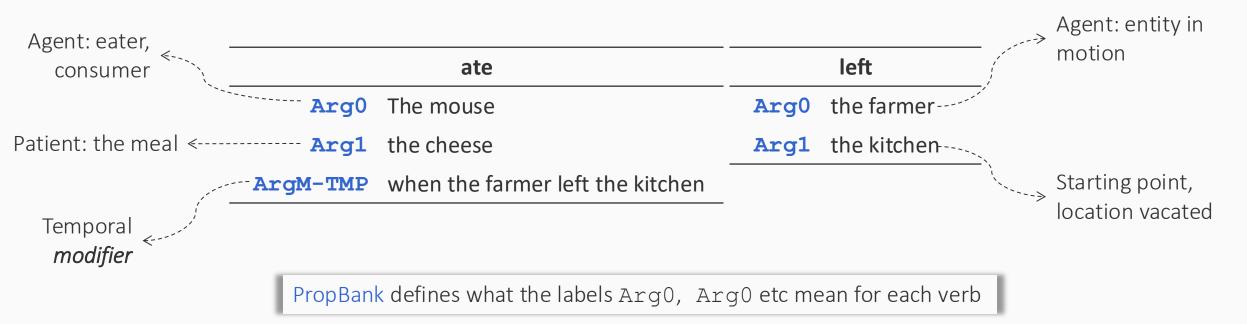
#### What do the labels mean?

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#### What do the labels mean?

The mouse ate the cheese when the farmer left the kitchen.



# Semantic Role Labeling: The modeling problem

- Input: A sentence
- **Output**: Semantic frames for all verbs

A well studied task, large datasets in English

- Penn Treebank data, Ontonotes annotated with PropBank roles
- Creating datasets is not easy though

# Semantic Role Labeling: The modeling problem

- Input: A sentence
- **Output**: Semantic frames for all verbs

The output is *structured*, and has constraints about the labels. For example

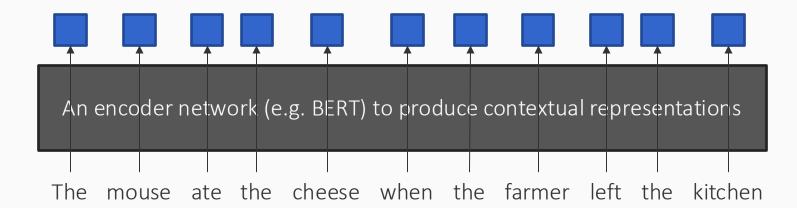
- Core arguments (e.g. Arg0, Arg1) cannot repeat...
  - ...but modifiers (e.g. ArgM-TMP) can
- Certain arguments (called references, e.g. R-Arg0) can appear only if the corresponding referent argument exists (here, Arg0)

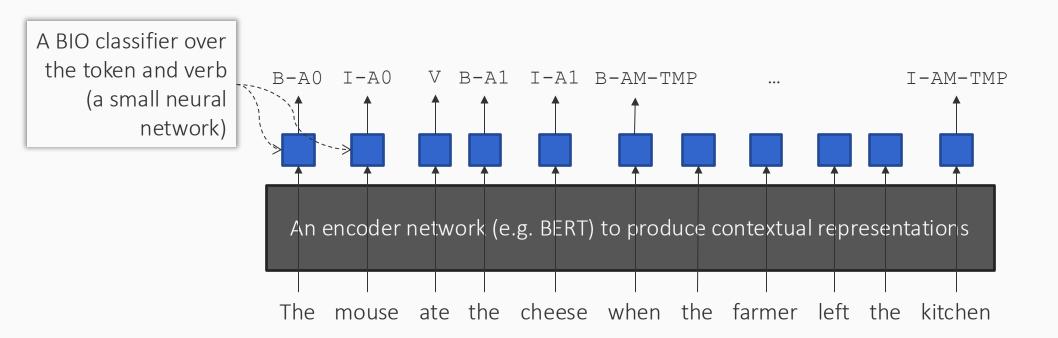
*These symbolic constraints come from the task definition. And linguistic assumptions. We will see other constraints later* 

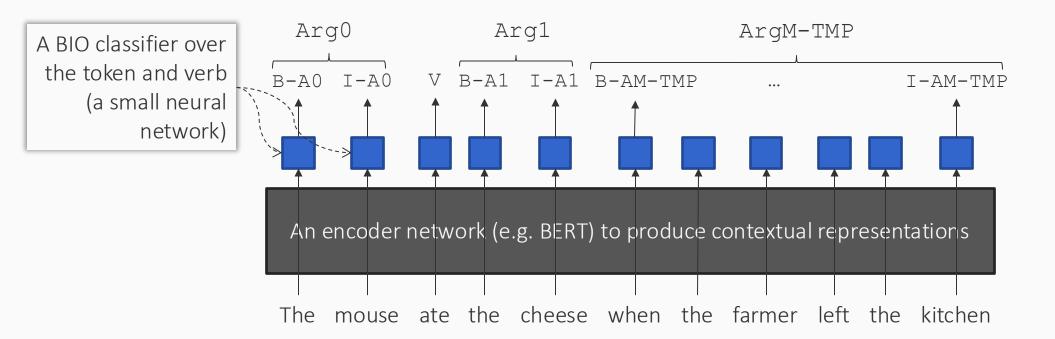
#### A common design of neural SRL models

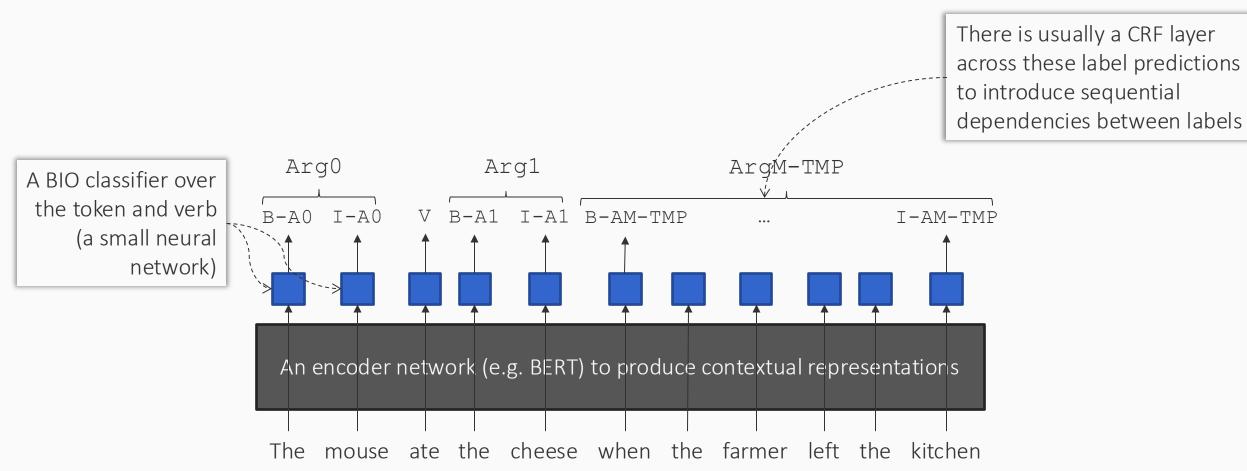
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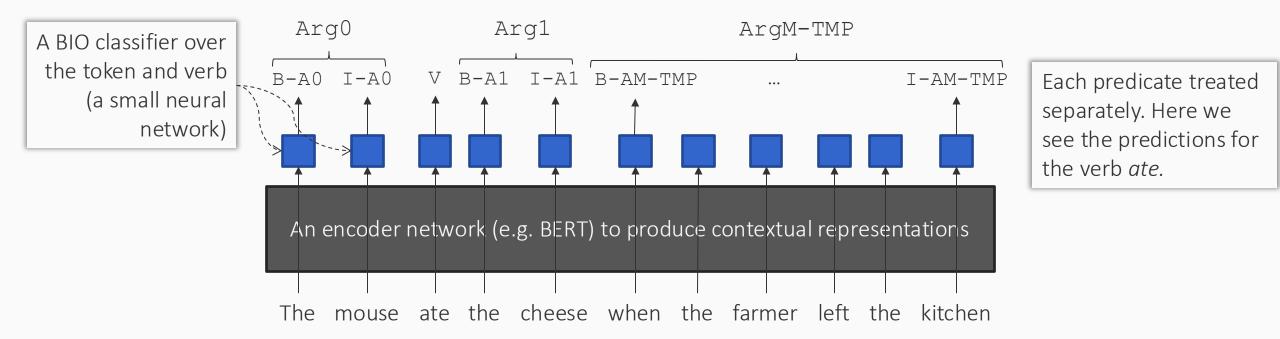
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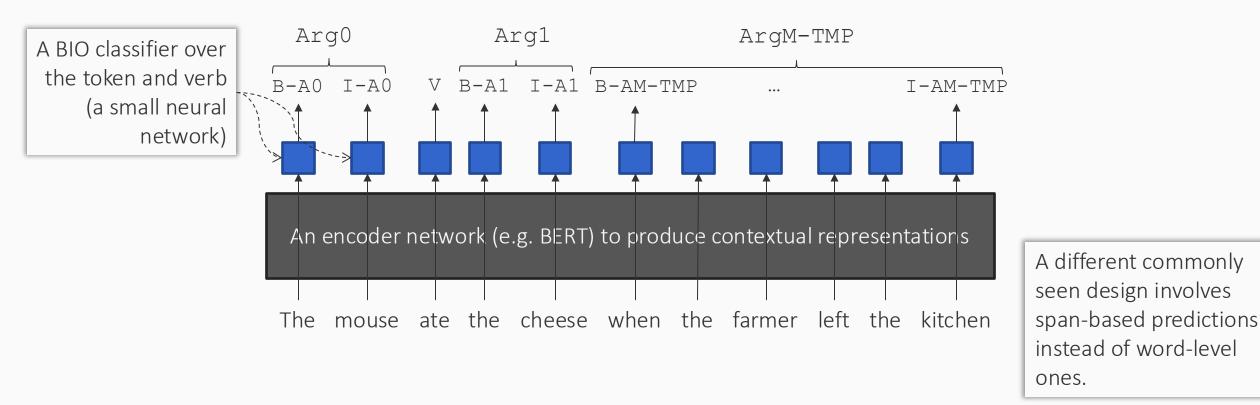




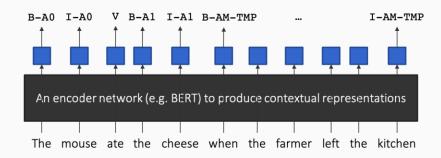








### A remarkable class of models!



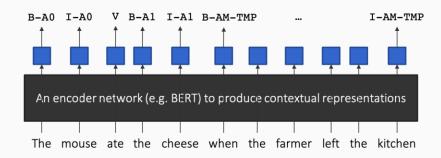
These models are excellent in terms of predictive accuracy

- E.g. with RoBERTa embeddings, on Wall Street Journal data, we can get ~88% F-scores
- And ~80% on out of domain (Brown corpus) sentences

Impressively, they do so with no information about the output space

- No symbolic constraints prohibiting invalid labels
- No structural information about references, etc
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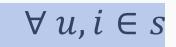
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Is there room for knowledge in the form of symbolic constraints in neural SRL models?

- If so, how do we introduce it without sacrificing modeling convenience?

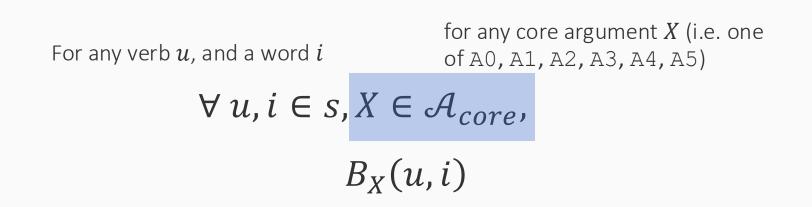
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 $\forall u, i \in s$  $B_X(u, i)$ 

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for any core argument X (i.e. one of A0, A1, A2, A3, A4, A5)

$$\forall u, i \in s, X \in \mathcal{A}_{core},$$
$$B_X(u, i) \to \bigwedge_{\substack{j \in s \\ j \neq i}}$$

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The model cannot predict that it is the beginning of the same label

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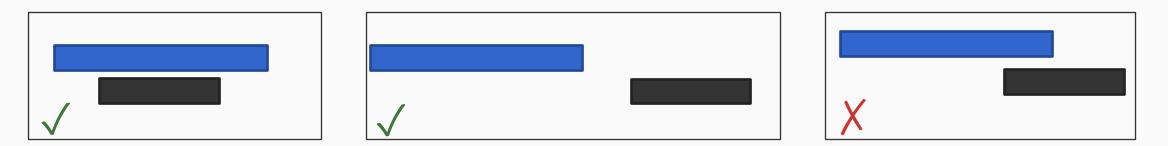
Then, for any other word j

j≠i

### Other constraints (informally)

#### The exclusively overlapping role constraint:

 In any sentence, an argument for a predicate can either be contained in, or fully outside, the argument for any predicate



#### The frame core role constraint

- A verb can have only those core arguments that are defined in PropBank

### The modeling questions

How can we incorporate such knowledge into our modeling and/or prediction process?

- The constraints are not dependent on any specific labeled example
- The labeled data presumably already satisfies the constraints

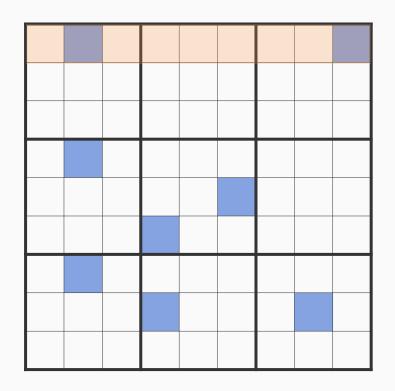
Can such knowledge help?

### Let's look at a few examples

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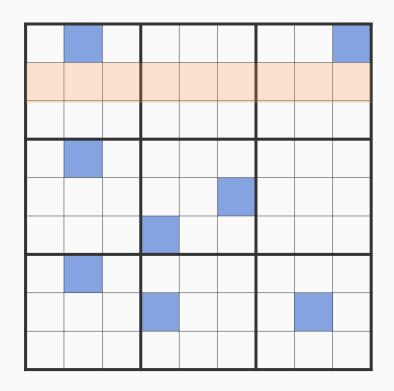
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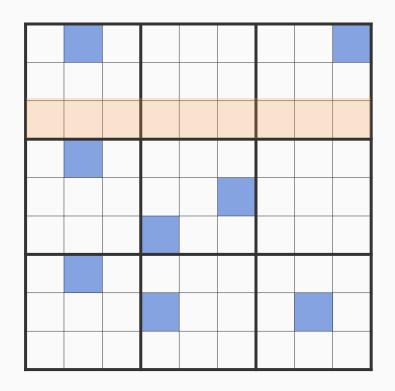
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Example: sudoku



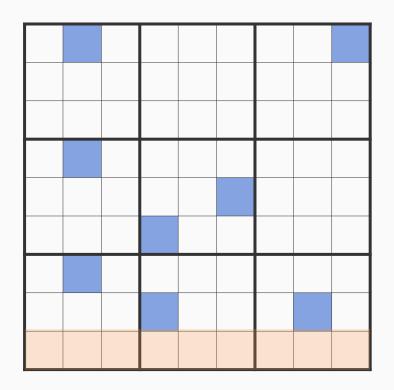
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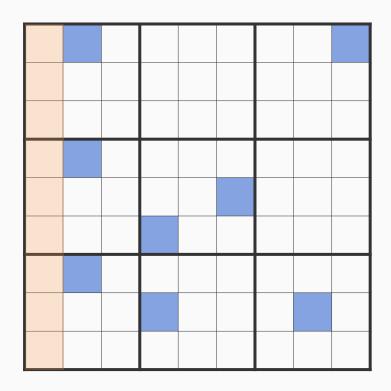
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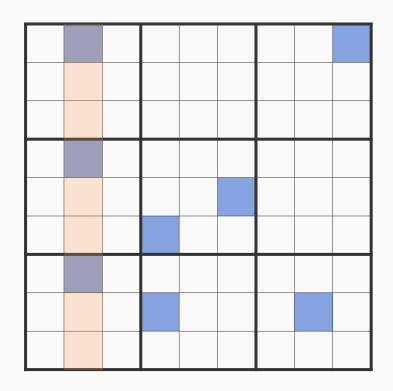
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We have nine rows in all



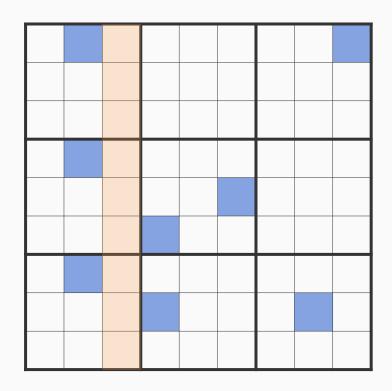
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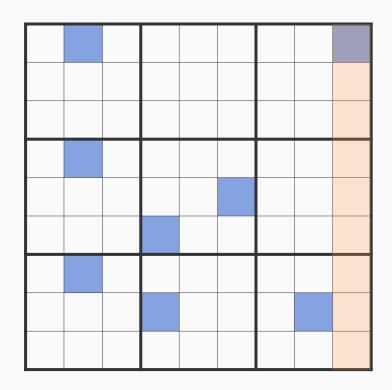
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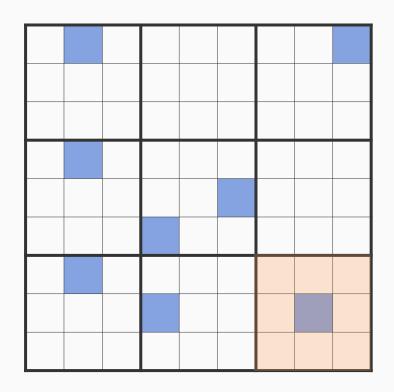
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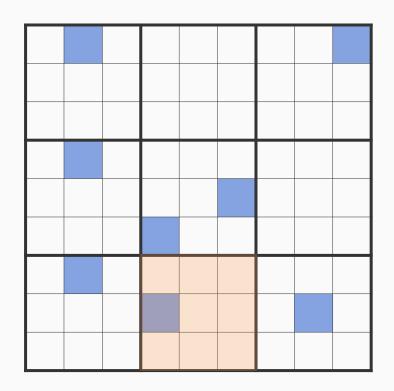
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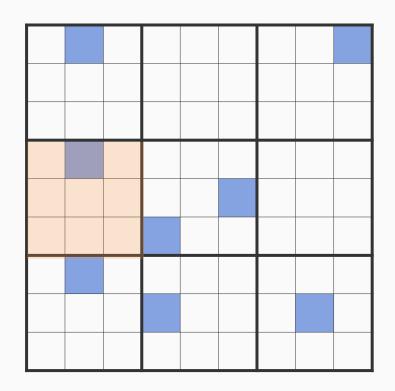
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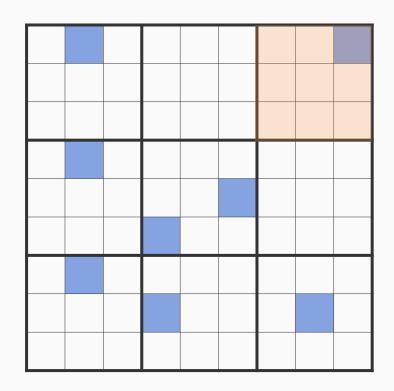
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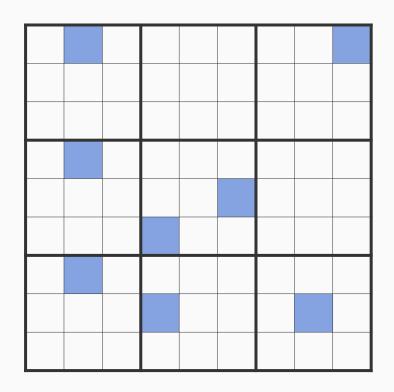
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### A neural network that can solve sudoku?

Can we train a neural network to solve a sudoku?

Can we do so without any training examples, with only the rules of the game (expressed formally)?

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Note: Sudoku is an example of a constraint satisfaction problem. We don't need to train a neural network to solve the problem.

For the purpose of this course, we are asking these questions to demonstrate what *can* be done, not necessarily what *should* be done

### Let's look at a few examples

- 1. Recognizing digits and adding them
- 2. Semantic role labeling
- 3. Using the rules of a game to play the game
- 4. Other examples

#### Other motivating examples

Can we construct a knowledge base using facts learned from the internet and also knowledge about the world such as "The father of a father is a grandfather"?

Can we write a program that operates over multiple independent large language model predictions to produce an output that is consistent with some pre-defined rules?

Can we train a neural network with only a limited amount of training data for a task, given that we have some knowledge about the task?