Neural Inference of API Functions from Input-Output Examples

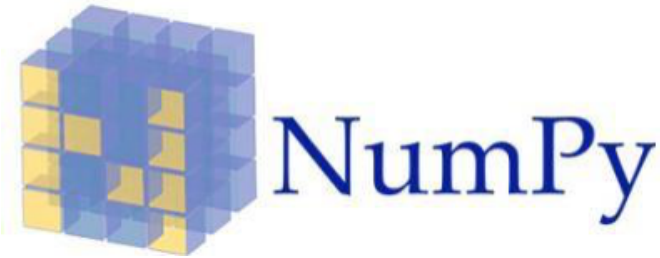
Rohan Bavishi, **Caroline Lemieux**, Neel Kant,
Roy Fox, Koushik Sen, Ion Stoica

Workshop on ML for Systems @ NeurIPS 2018

riselab
UC Berkeley

API Explosion!

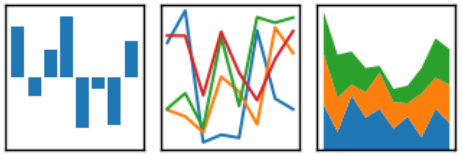
API Explosion!



API Explosion!

pandas

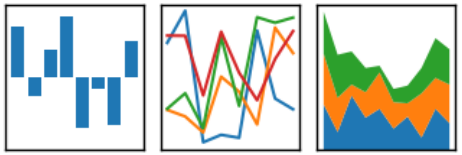
$$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$$

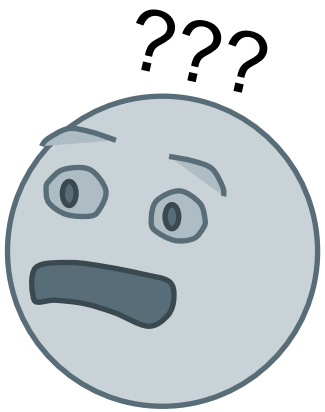


API Explosion!

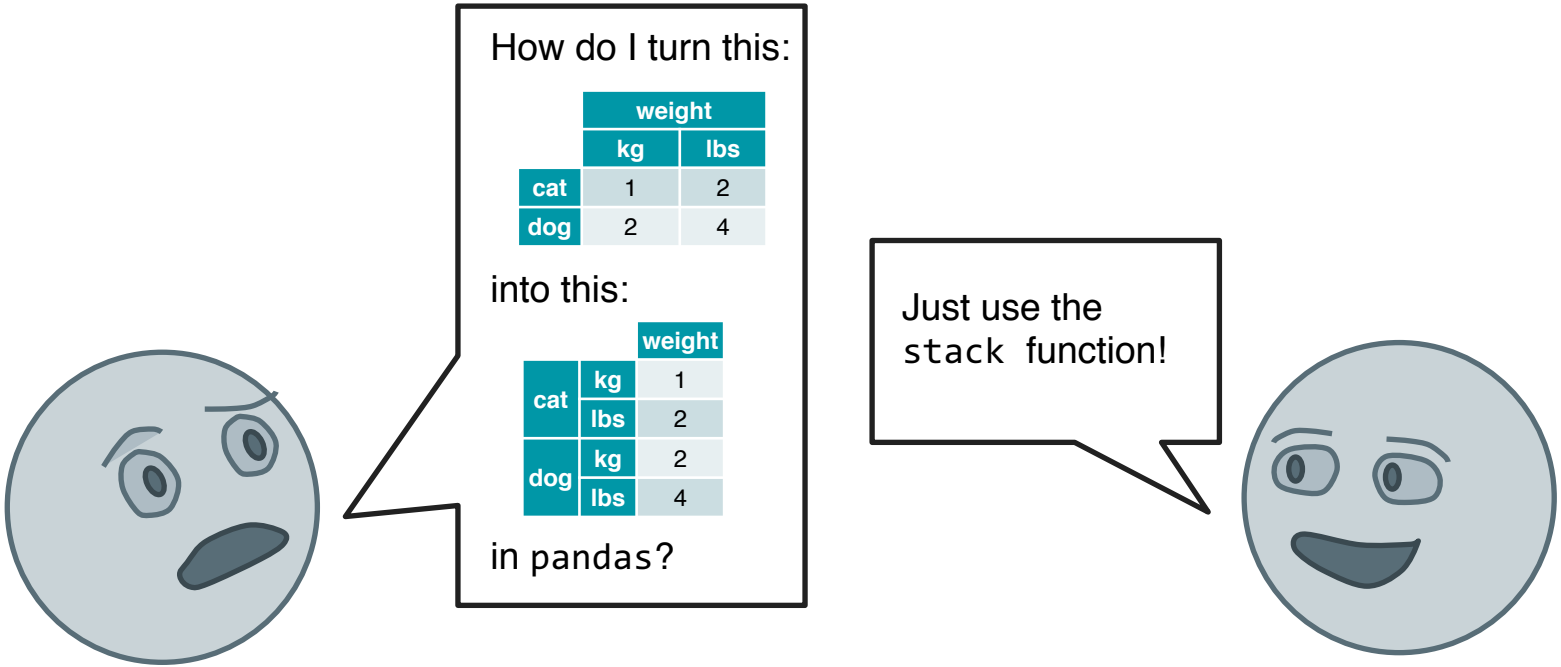
pandas

$$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$$

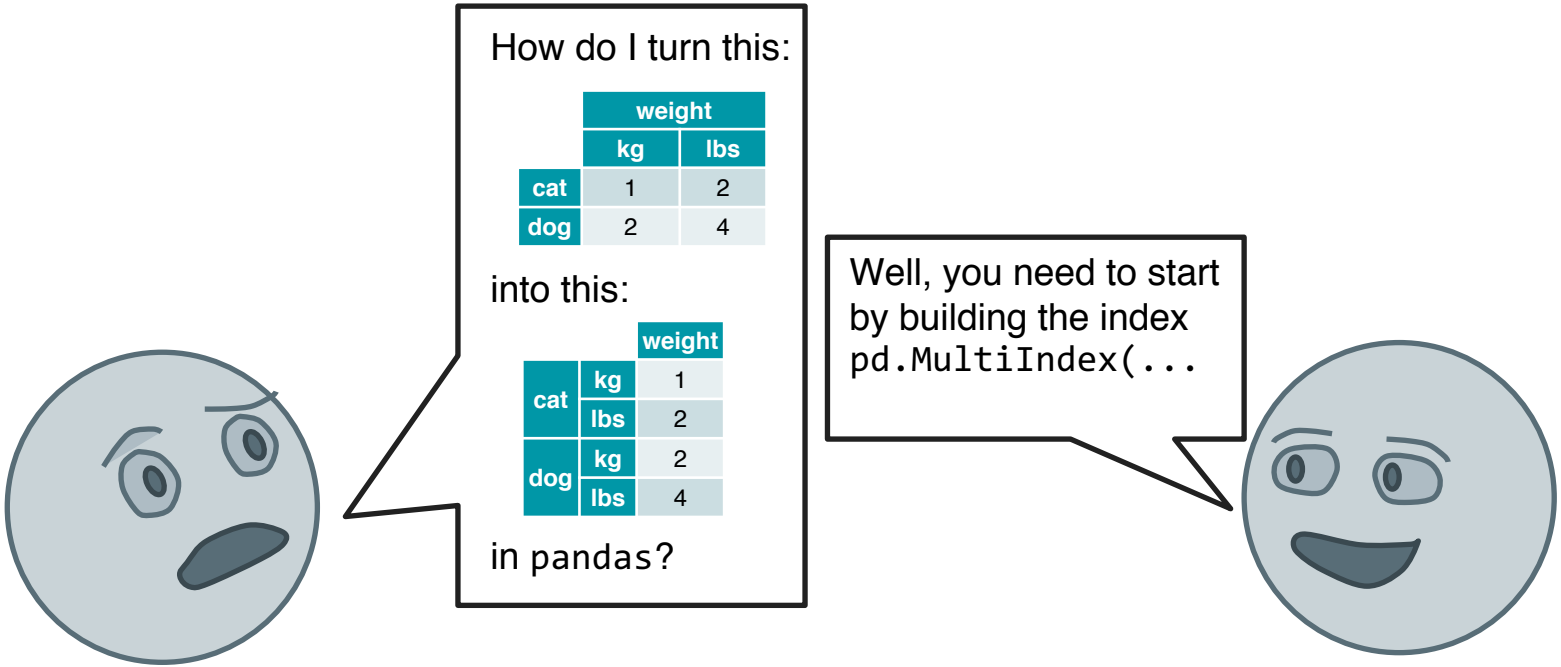




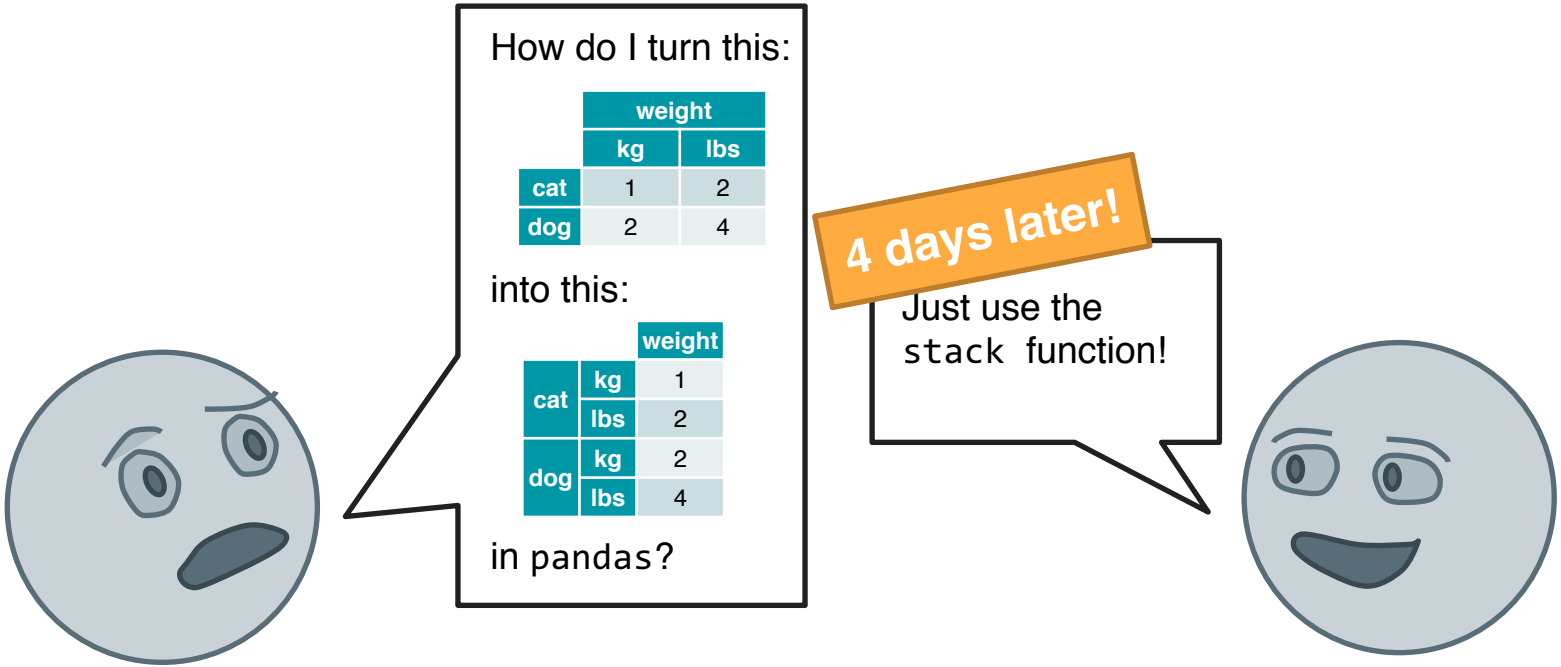
How to cope? *StackOverflow*



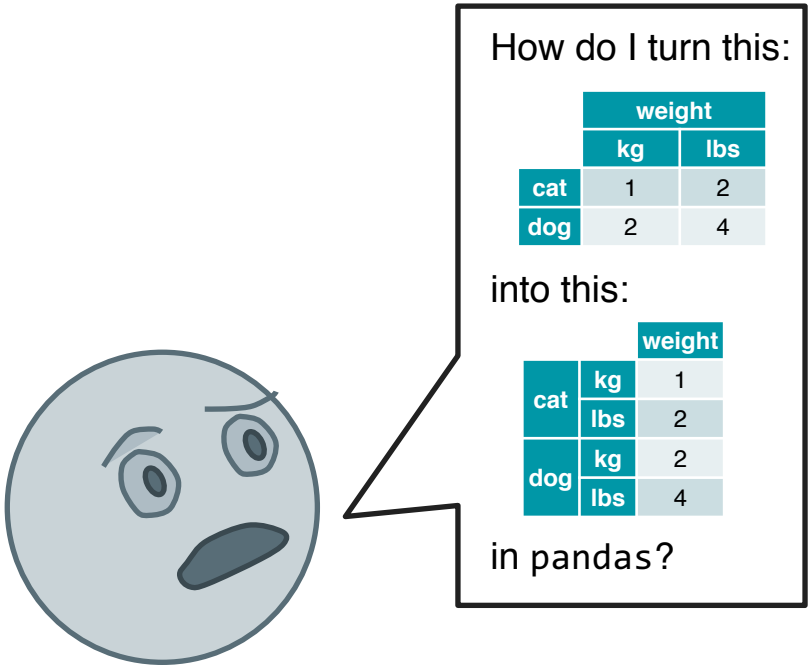
StackOverflow problems: Inefficient Solutions



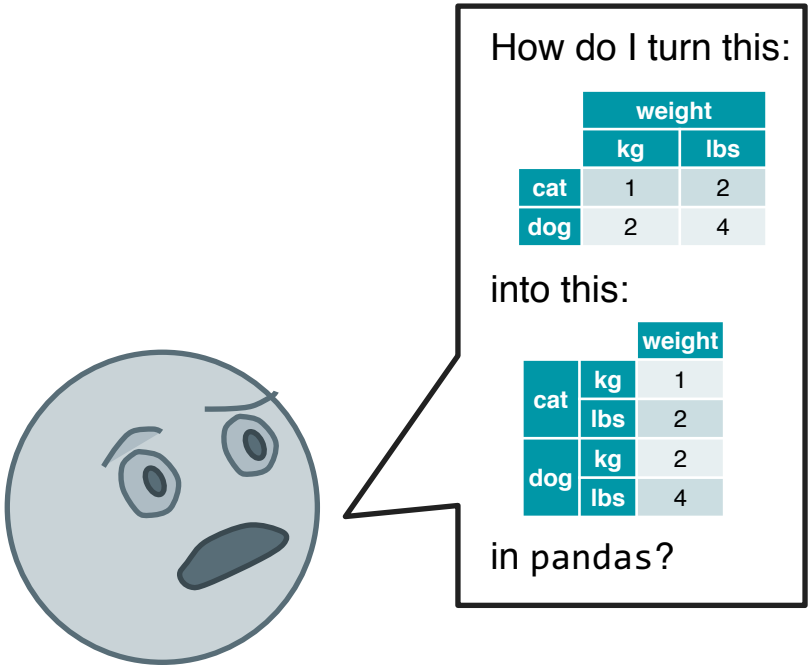
StackOverflow problems: Slow Response…

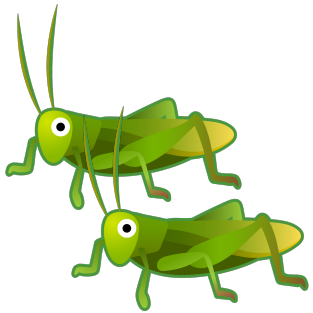


StackOverflow problems: No Response

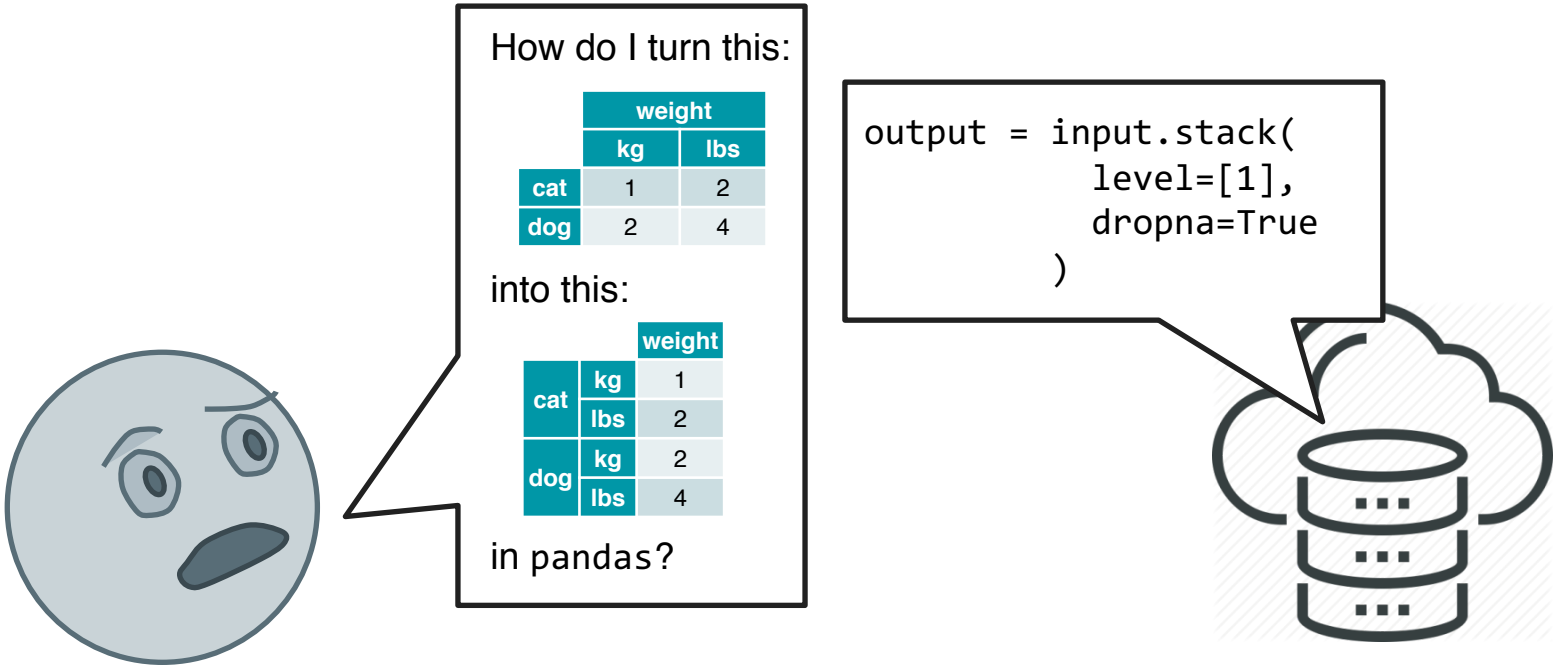


StackOverflow problems: No Response





Our Goal: Automate *StackOverflow* for APIs



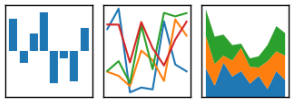
Technique Goals

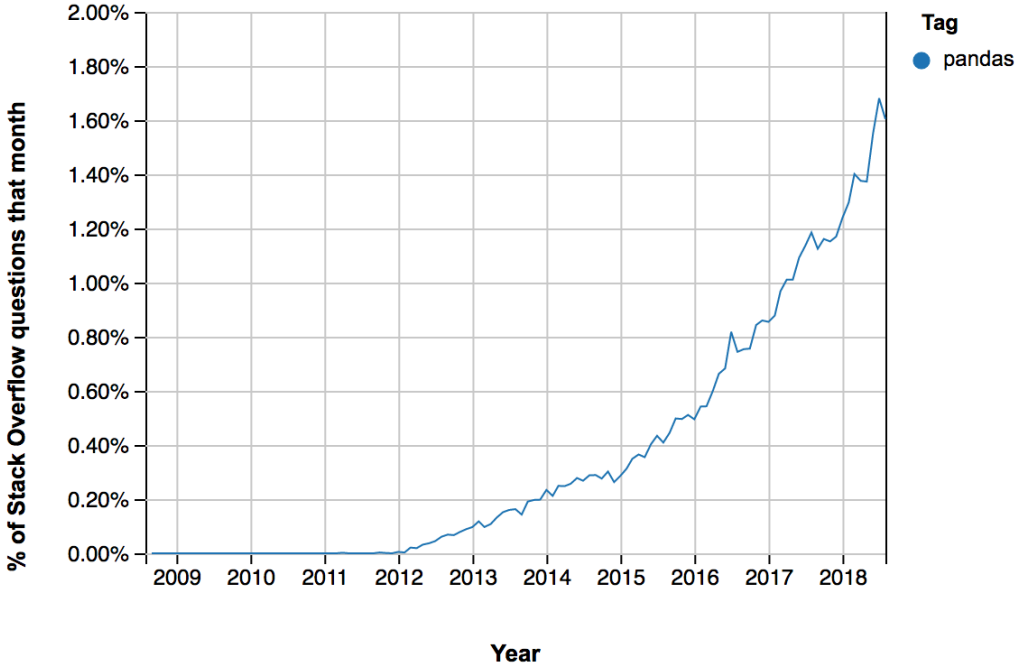
- Program synthesis engine in *realistic, wide* API (vs. narrow DSL)
- Scale to complex data structures
- Scale to 100s of functions, 1000s of arguments

First Target API: *pandas* library

pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

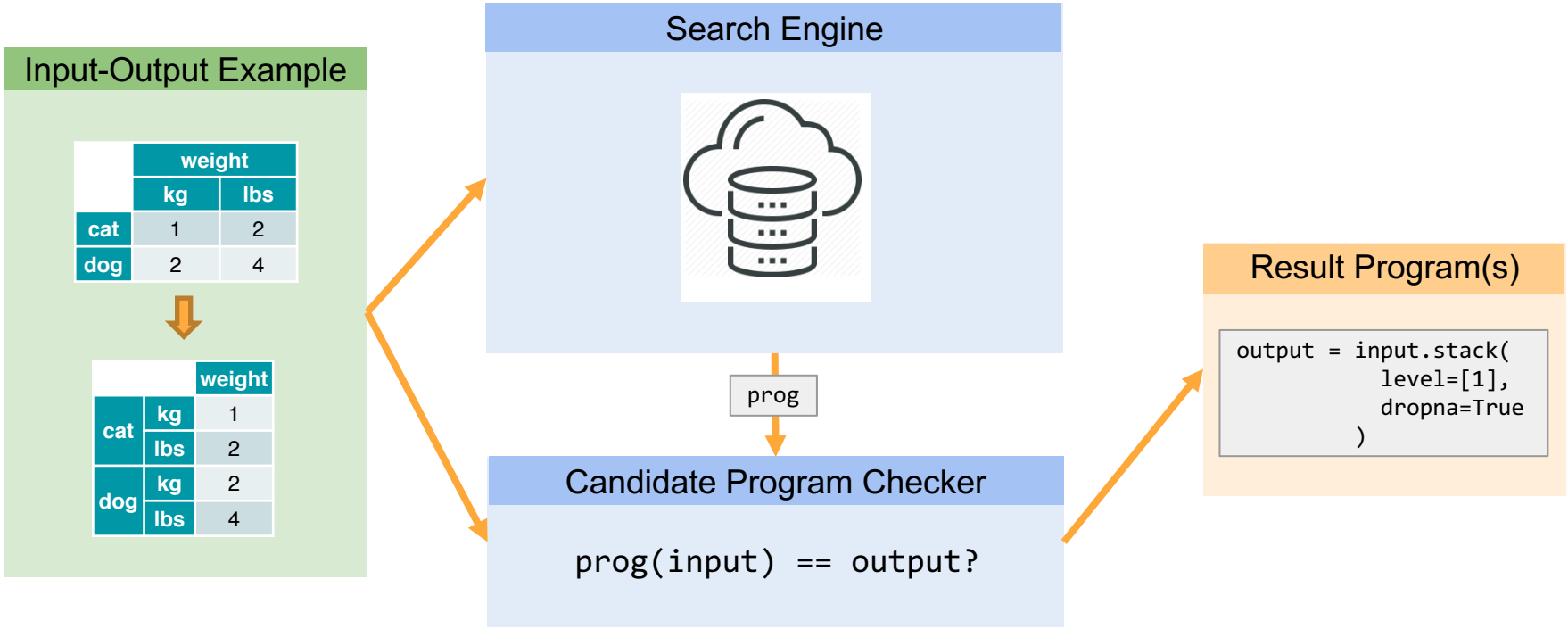




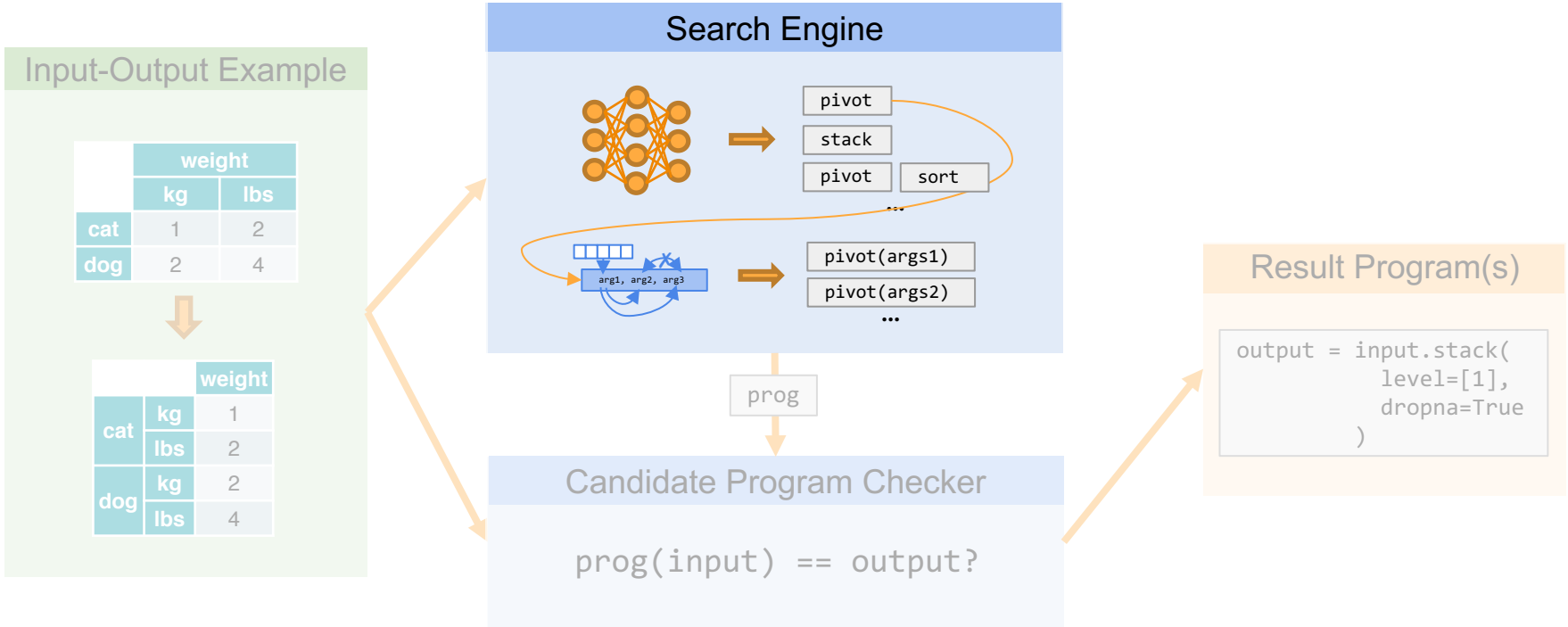
Technique Goals + *pandas*

- Program synthesis engine in *realistic* API
  - *Library of choice for data scientists*
- Scale to complex data structures
  - *DataFrames*
- Scale to 100s of functions, 1000s of arguments
  - ***10^{17}** branching factor for **depth 1**!*

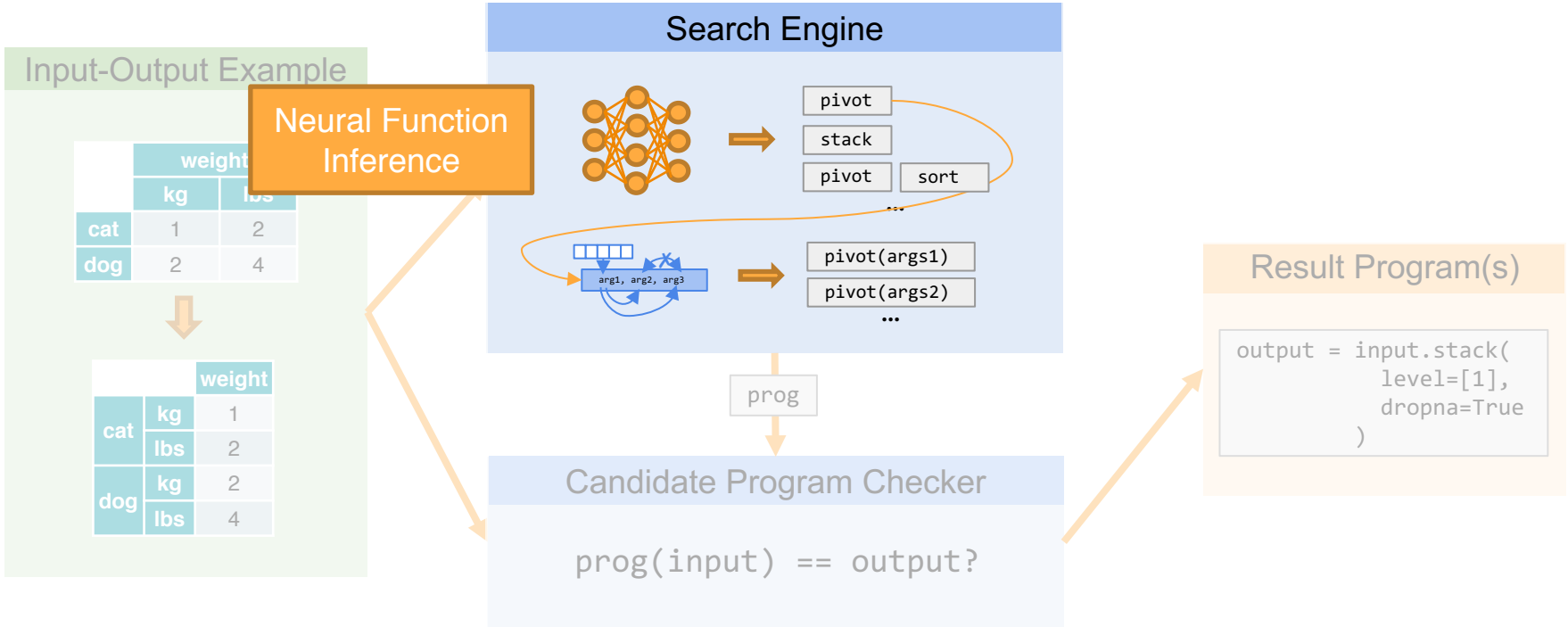
Synthesis Technique



Search Technique

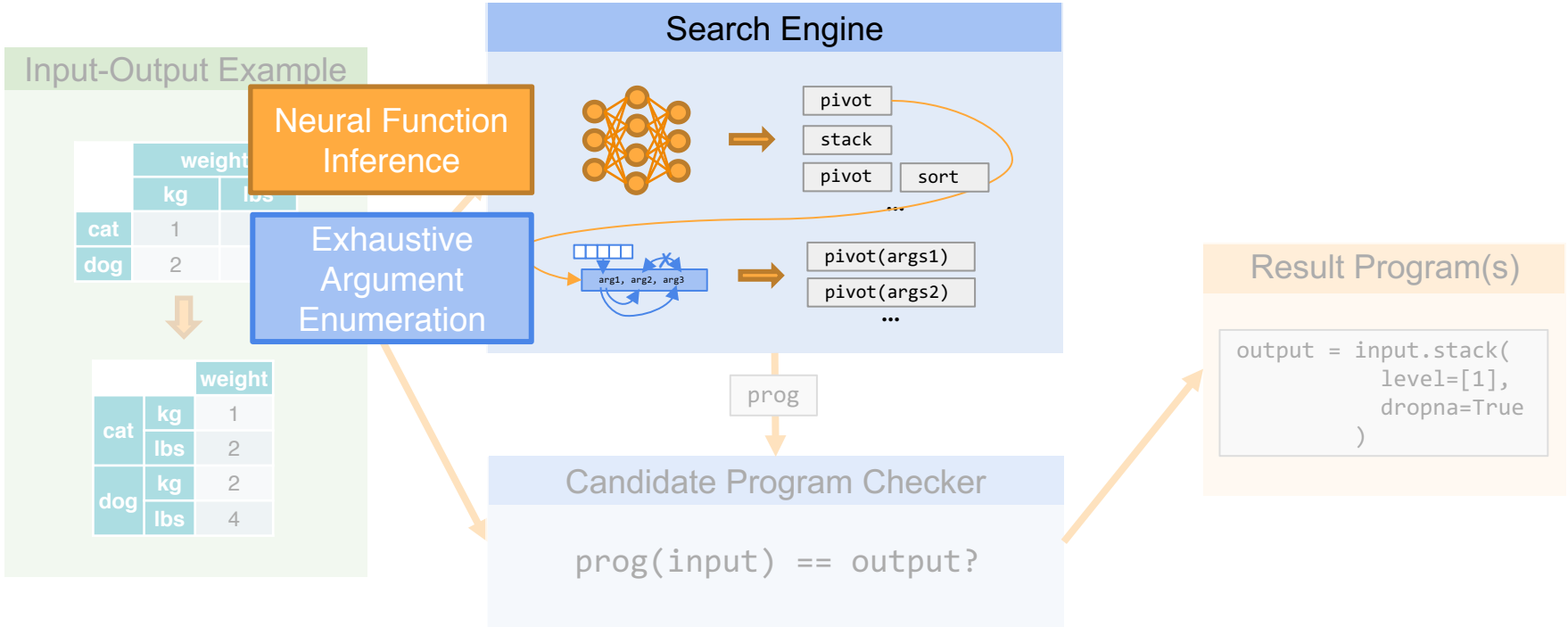


Search Technique Step 1

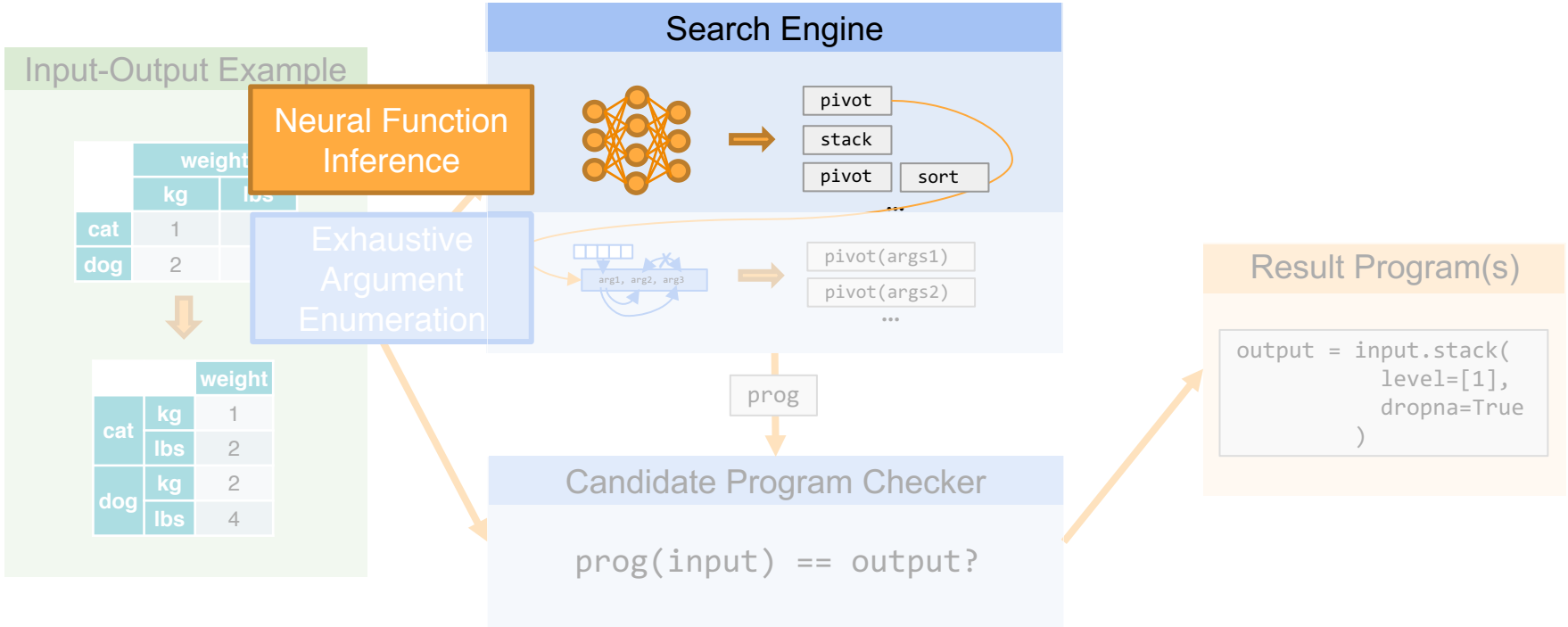


		weight
cat	kg	1
	lbs	2
dog	kg	2
	lbs	4

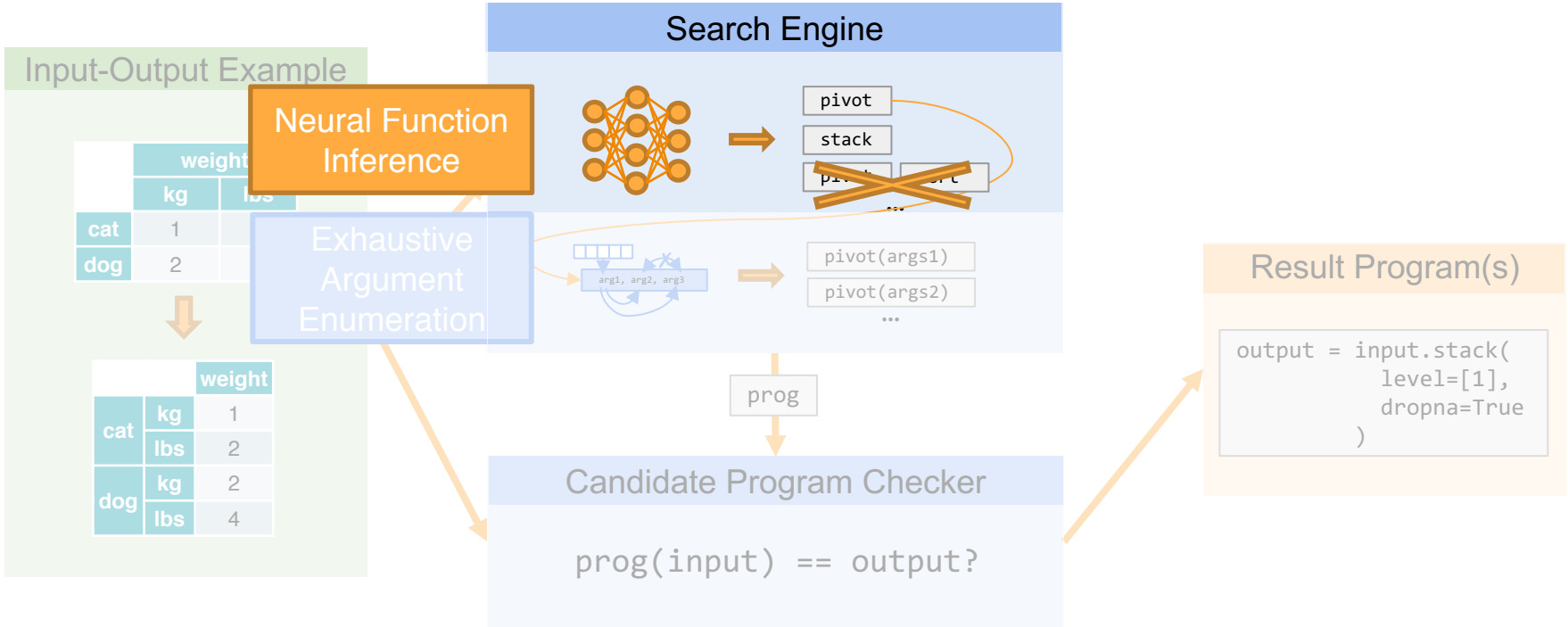
Search Technique Step 2



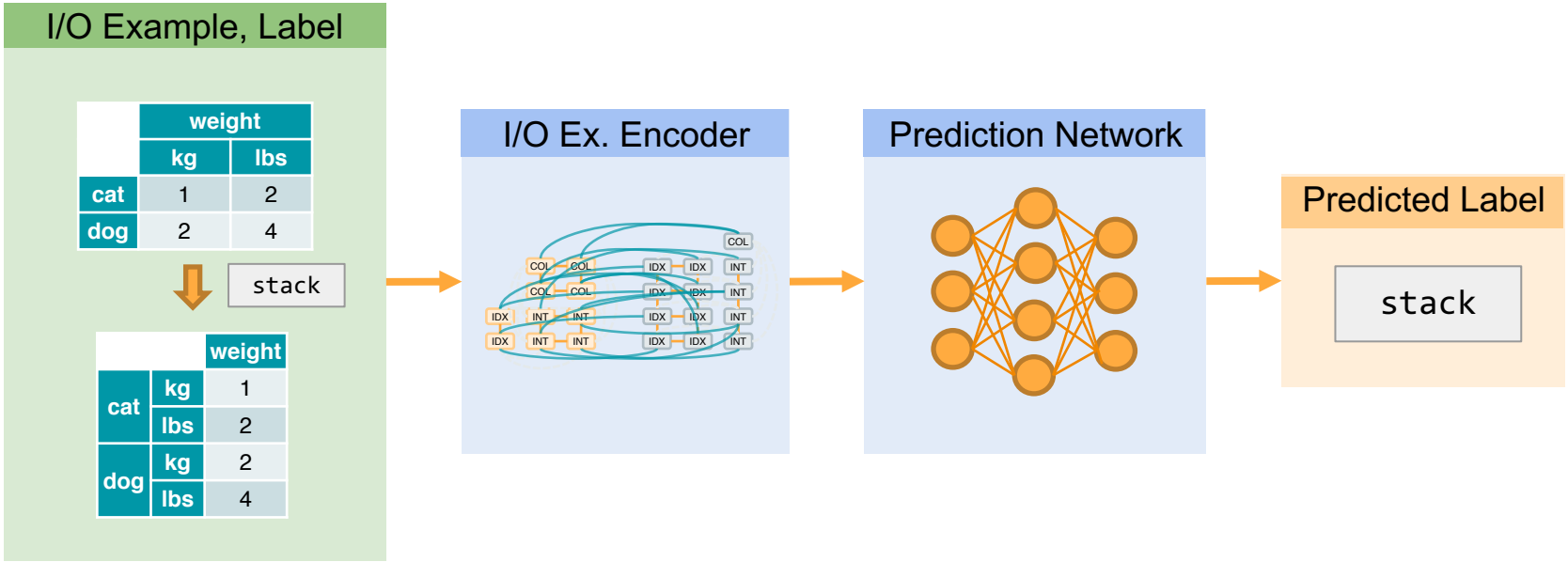
Focus: Neural Prediction Problem



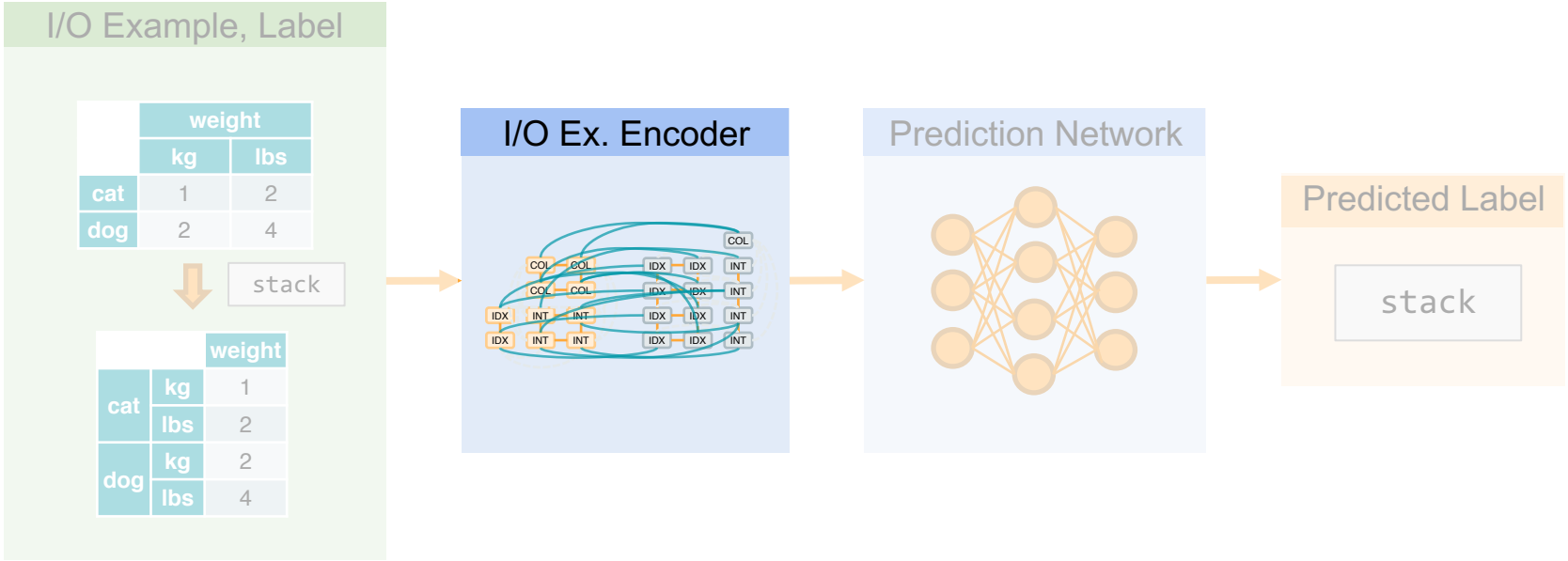
Focus: Neural Prediction Problem (Depth 1)



Zoom in: Neural Prediction Problem (Depth 1)

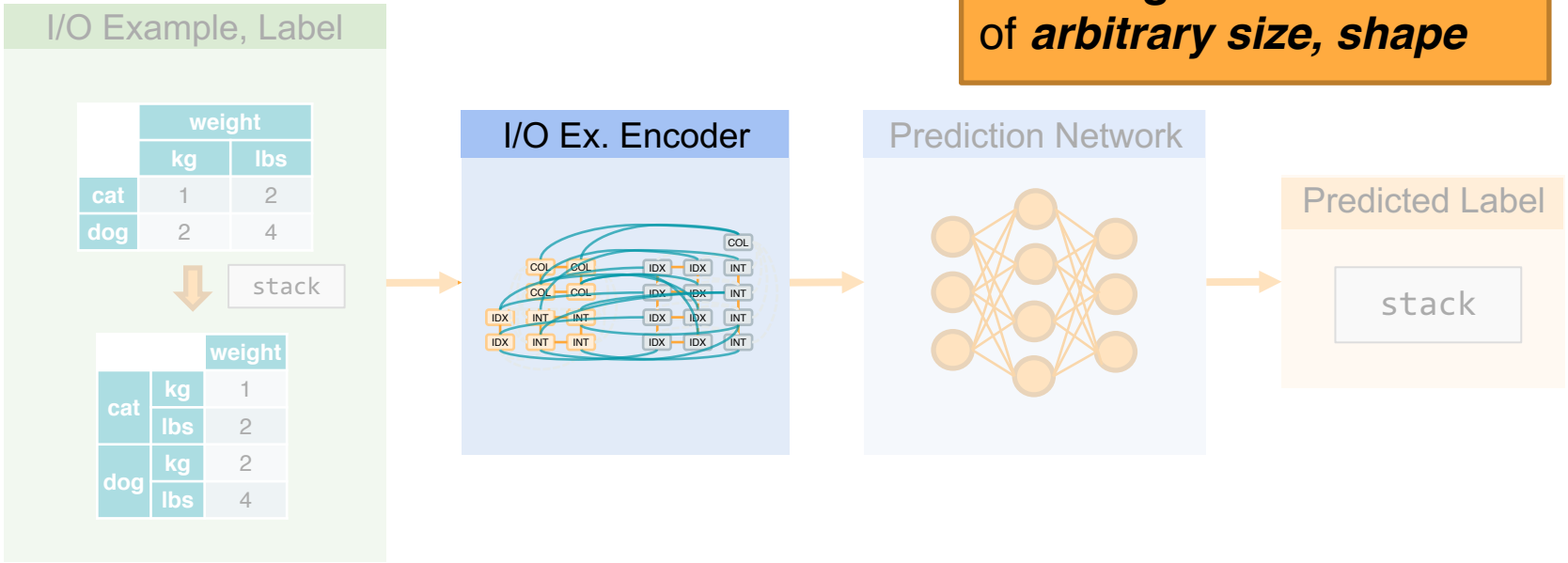


Step 1: Encoding I/O Example



Step 1: Encoding I/O Example

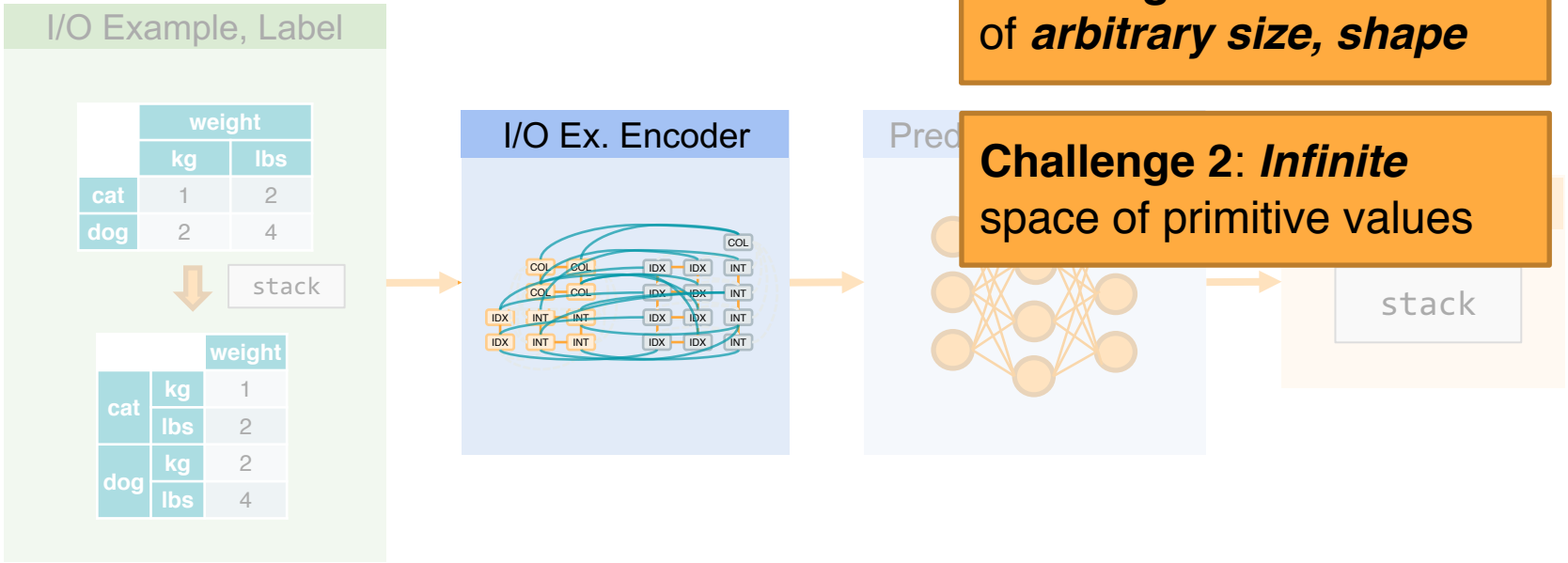
Challenge 1: DataFrames of ***arbitrary size, shape***



Step 1: Encoding I/O Example

Challenge 1: DataFrames of ***arbitrary size, shape***

Challenge 2: ***Infinite*** space of primitive values



Step 1: Encoding I/O Example

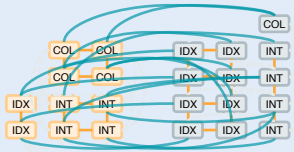
I/O Example, Label

	weight	
	kg	lbs
cat	1	2
dog	2	4

stack

		weight
cat	kg	1
	lbs	2
dog	kg	2
	lbs	4

I/O Ex. Encoder



Pred

Challenge 1: DataFrames of ***arbitrary size, shape***

Challenge 2: ***Infinite*** space of primitive values

Key observation: value ***relationships*** matter

Step 1: Encoding I/O Example

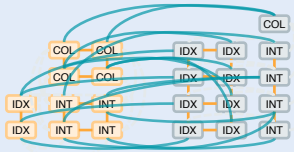
I/O Example, Label

	weight	
	kg	lbs
cat	1	2
dog	2	4

stack

		weight
cat	kg	1
	lbs	2
dog	kg	2
	lbs	4

I/O Ex. Encoder



Pred

Challenge 1: DataFrames of ***arbitrary size, shape***

Challenge 2: ***Infinite*** space of primitive values

Key observation: value ***relationships*** matter

Solution: ***graph-based*** encoding of I/O Example

Encoding an I/O Example as Graph

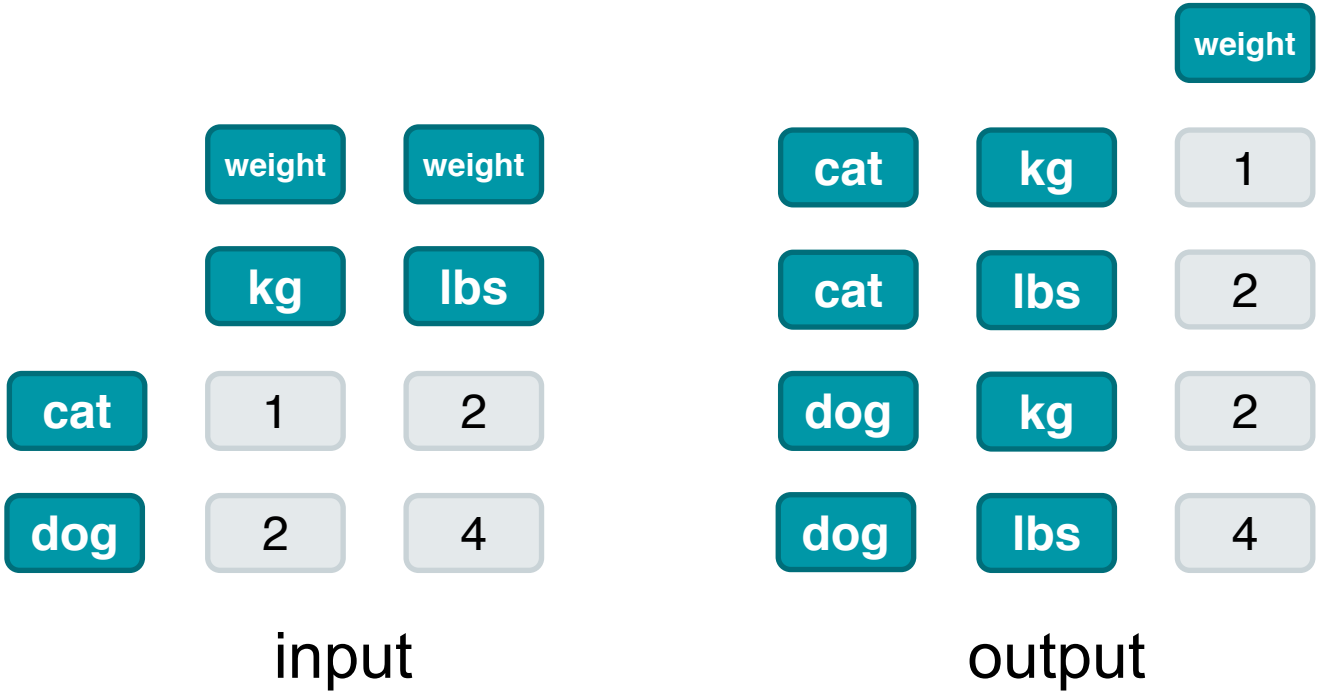
	weight	
	kg	lbs
cat	1	2
dog	2	4

input

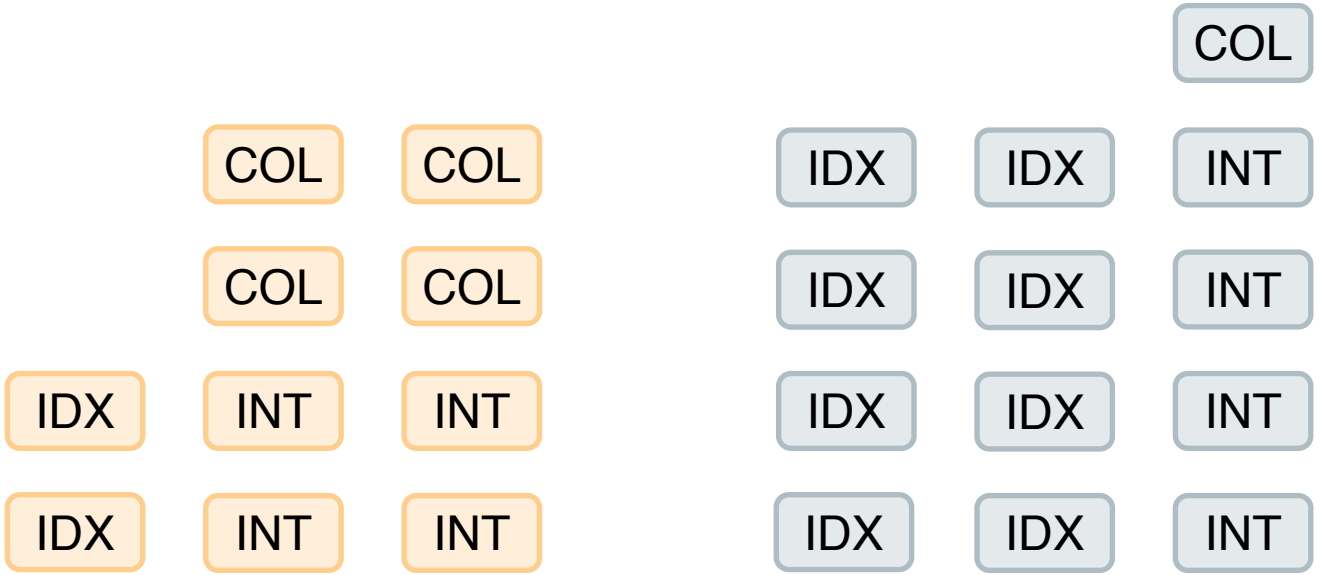
		weight
cat	kg	1
	lbs	2
dog	kg	2
	lbs	4

output

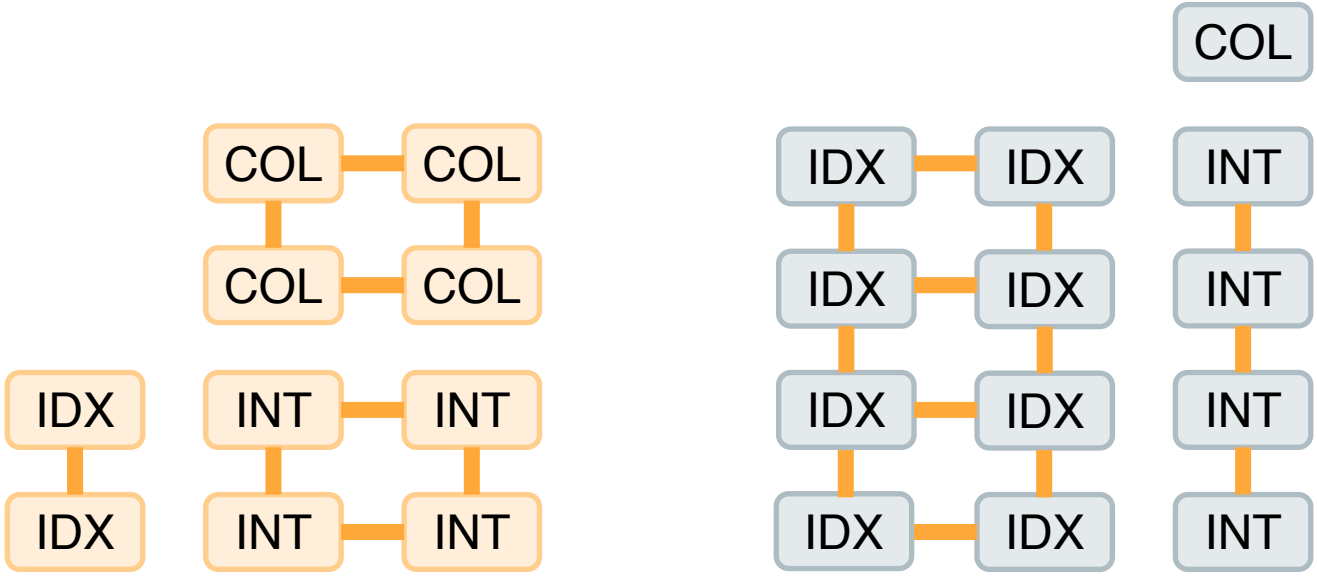
Encoding: Cells, Indices → Nodes



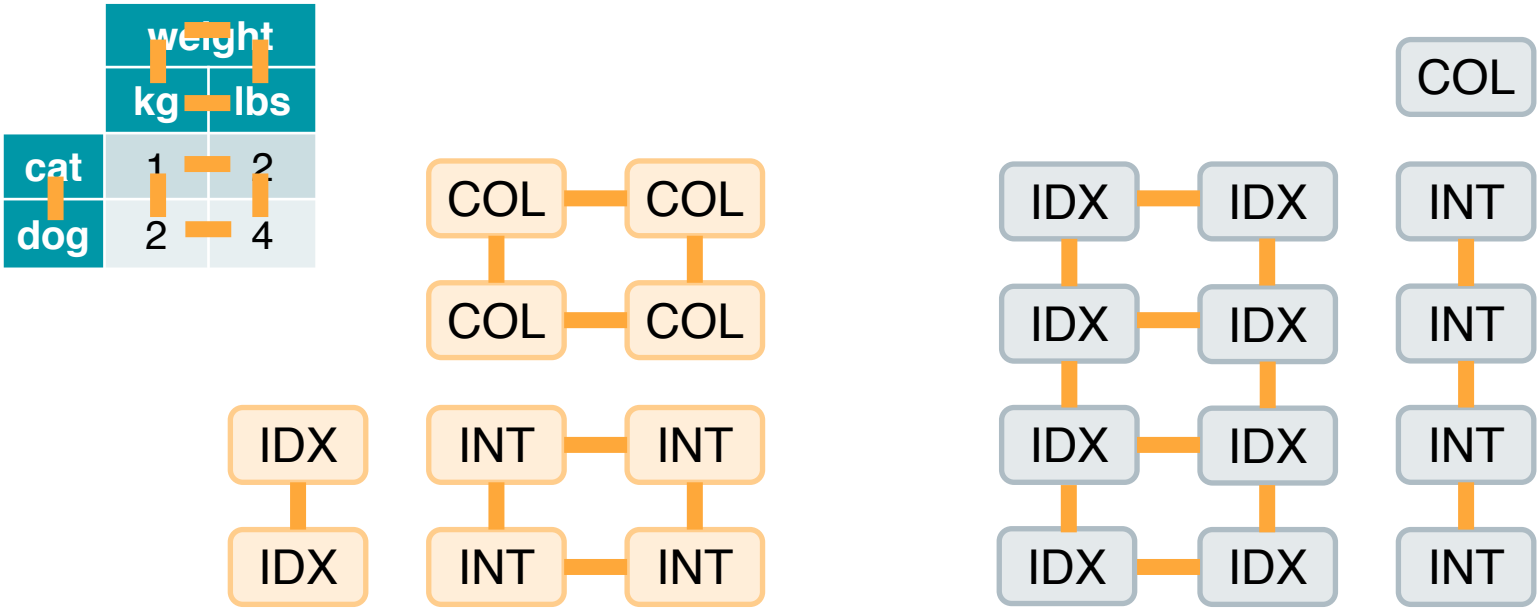
Encoding: Primitive Values → Types



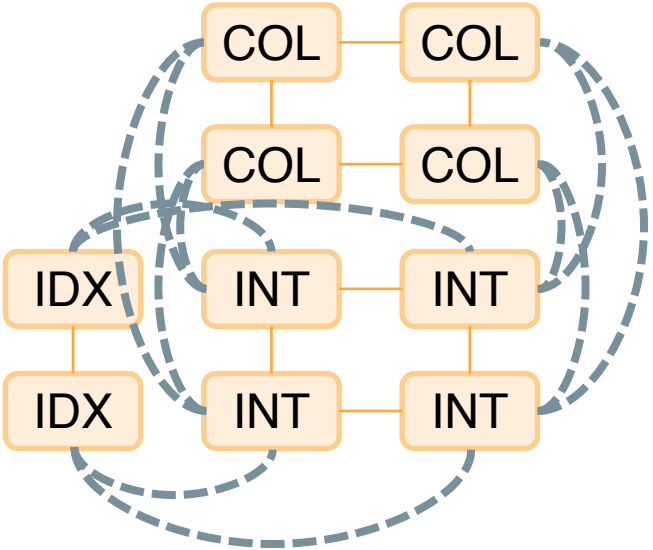
Encoding: *Adjacency* Edges

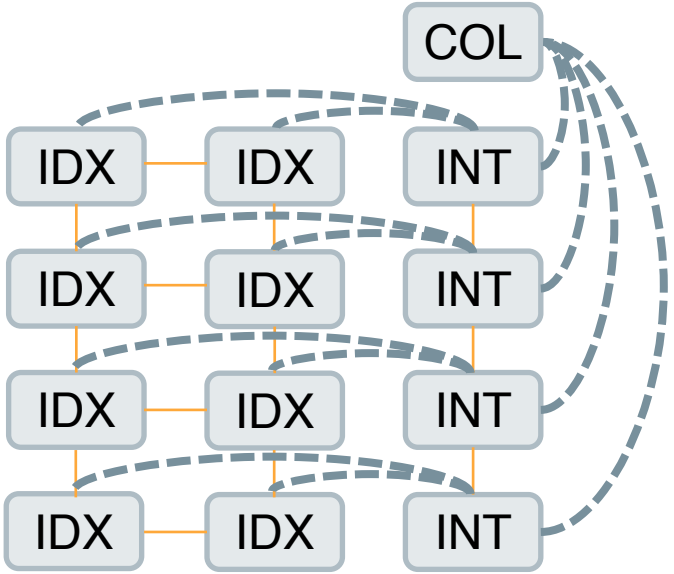


Encoding: *Adjacency* Edges



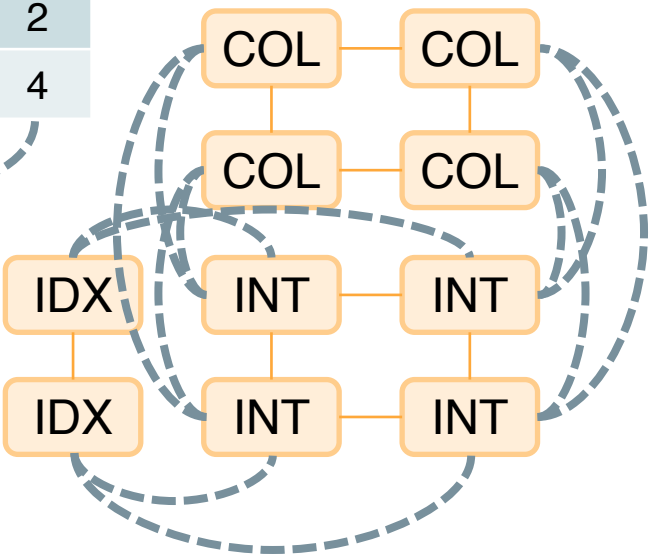
Encoding: *Indexing* Edges

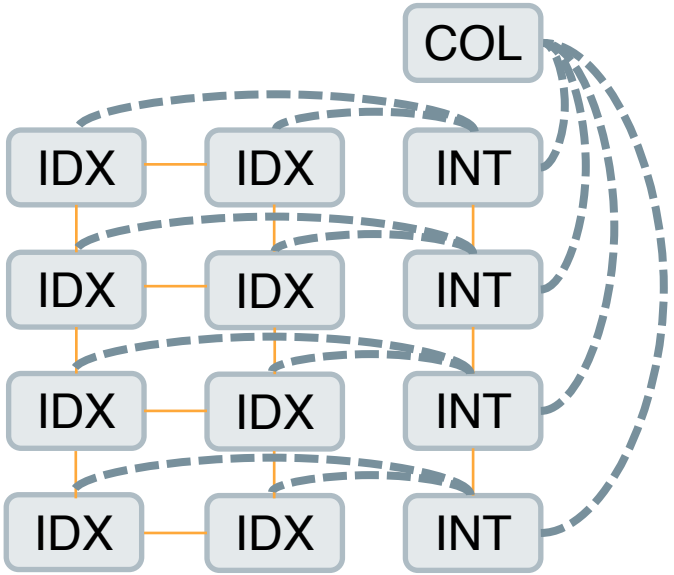




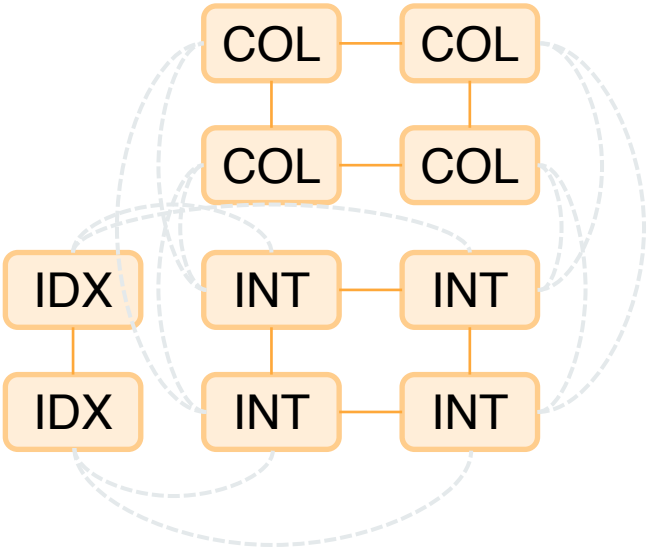
Encoding: *Indexing* Edges

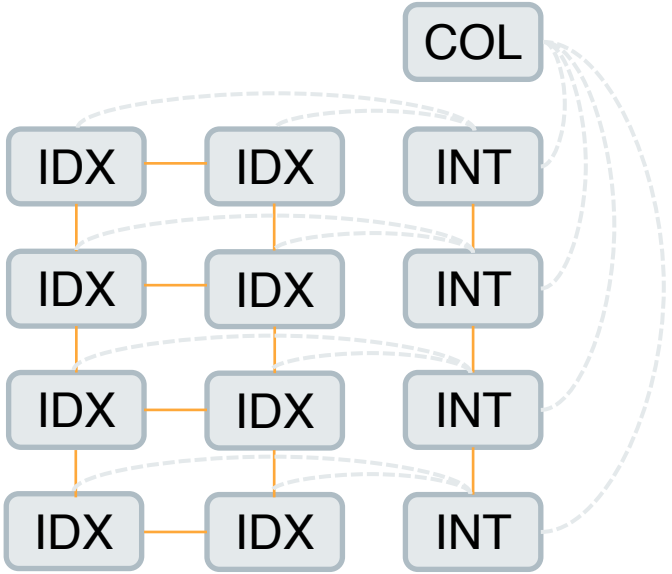
	weight	
	kg	lbs
cat	1	2
dog	2	4



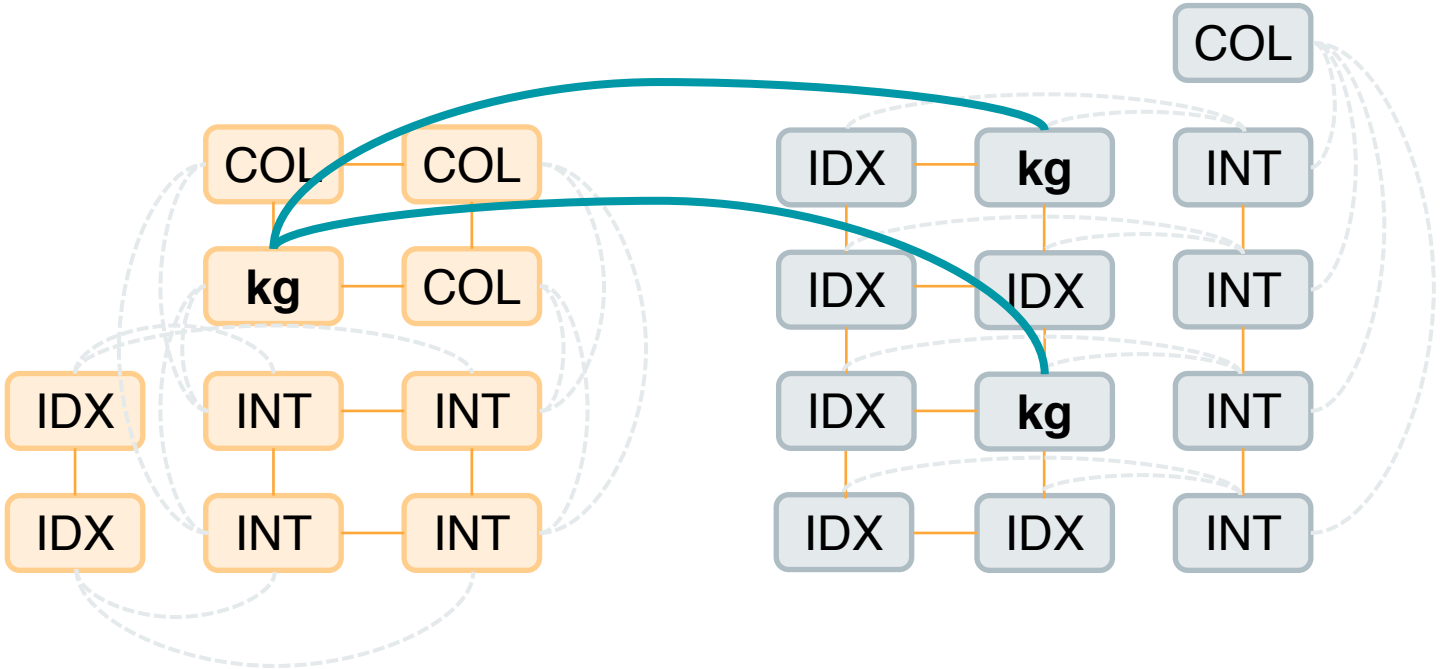


Encoding: *Equality* Edges

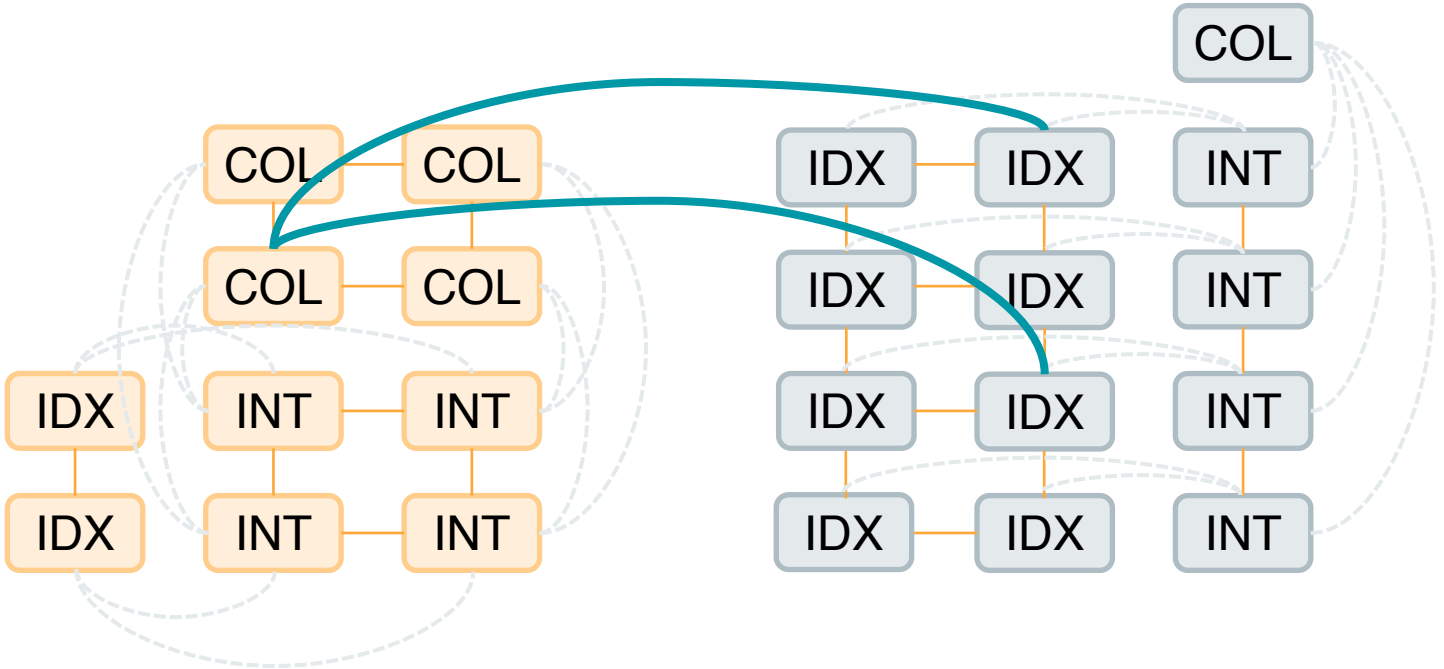




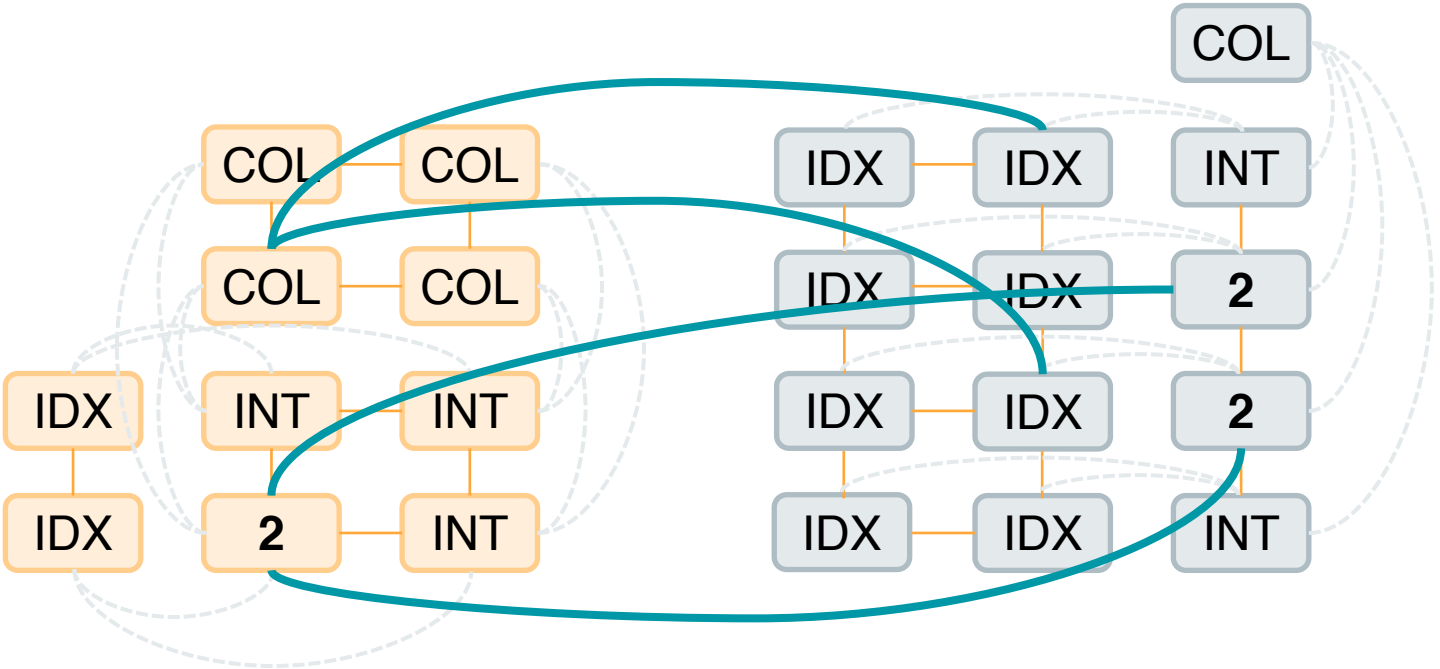
Encoding: *Equality* Edges



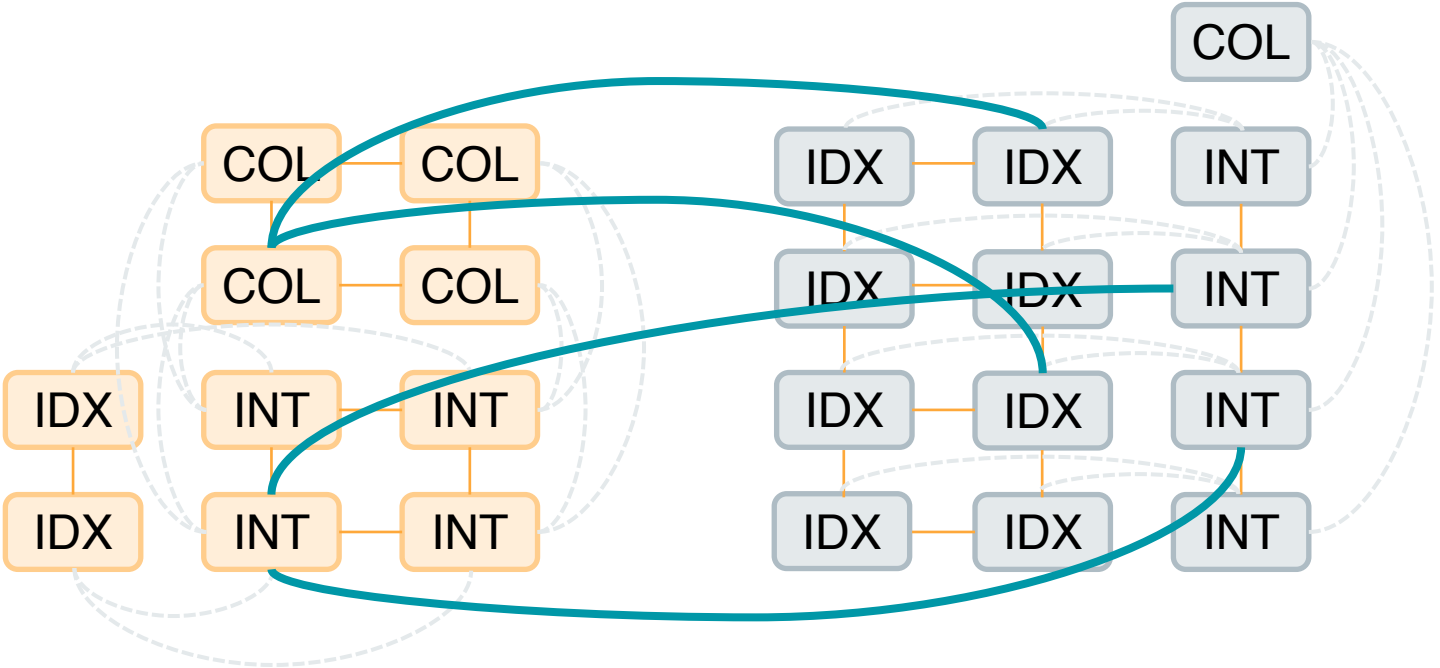
Encoding: *Equality* Edges



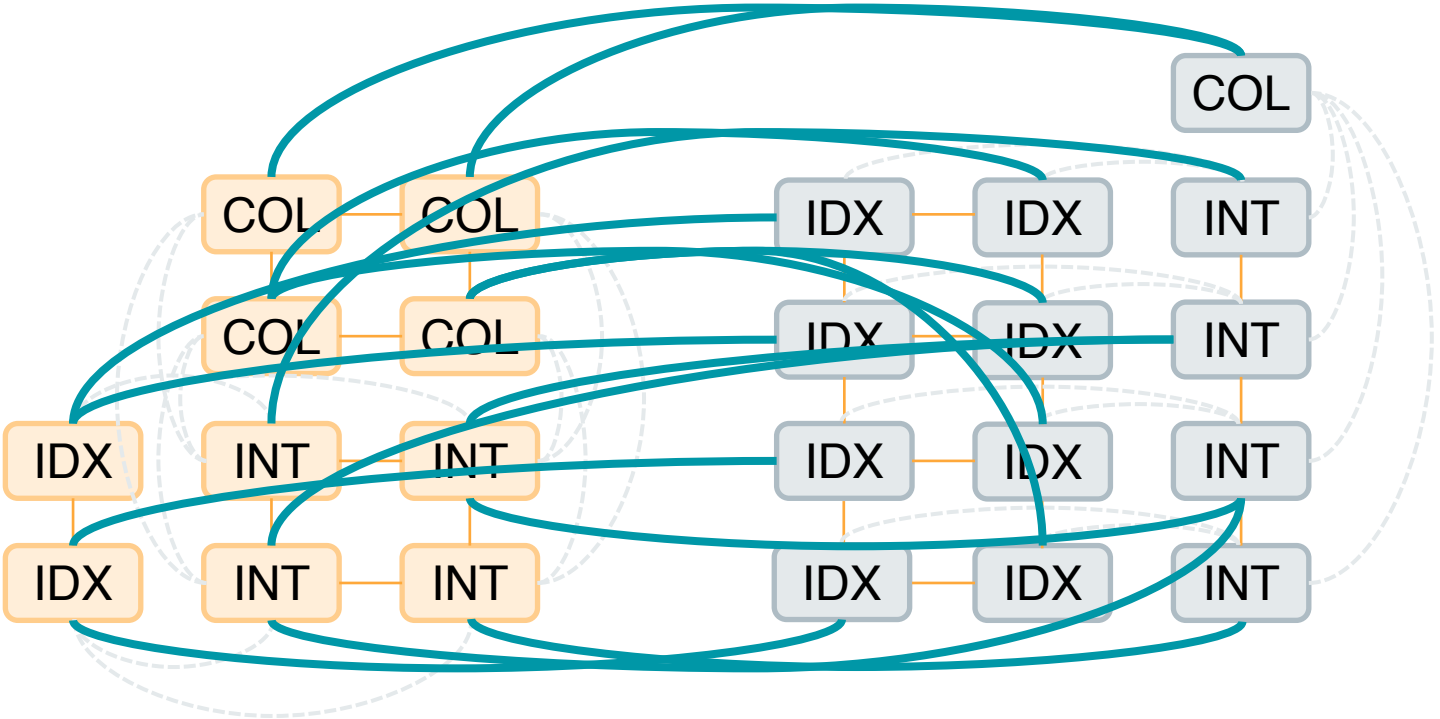
Encoding: *Equality* Edges



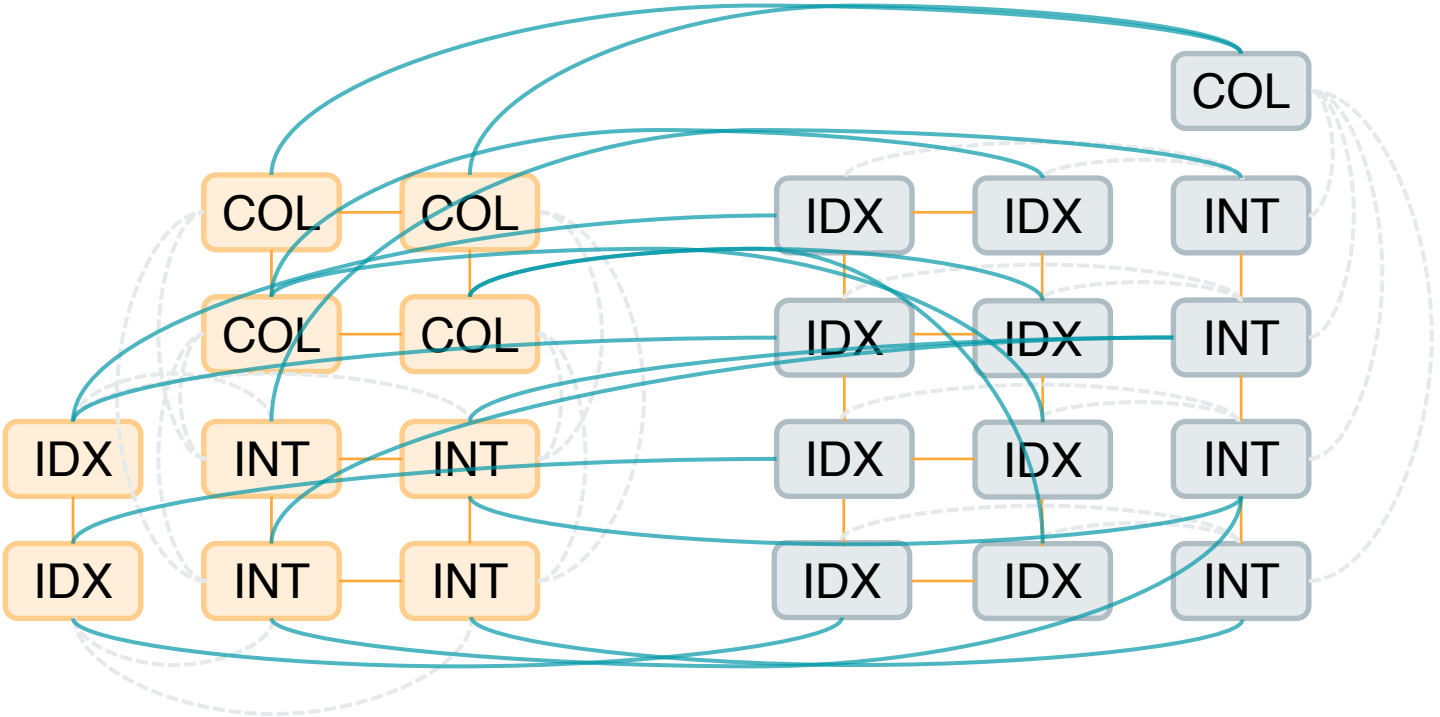
Encoding: *Equality* Edges



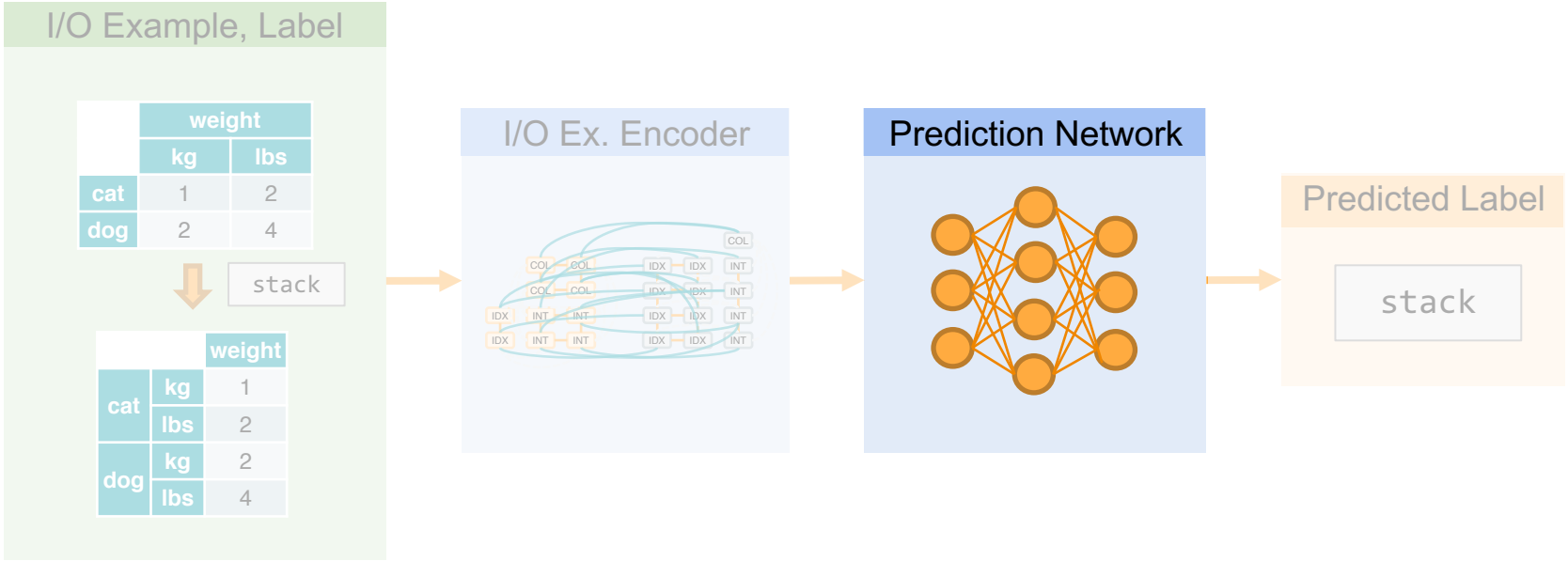
Encoding: *Equality* Edges



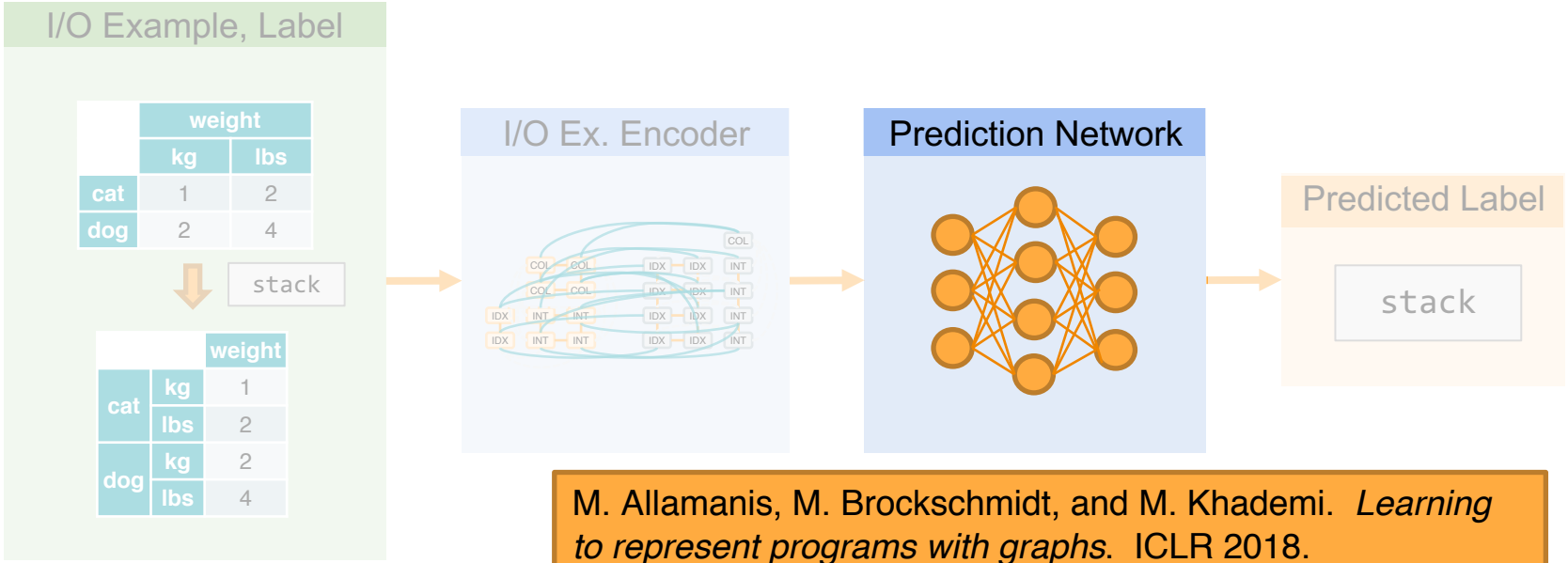
Final Encoding



Step 2: Predicting Function Label

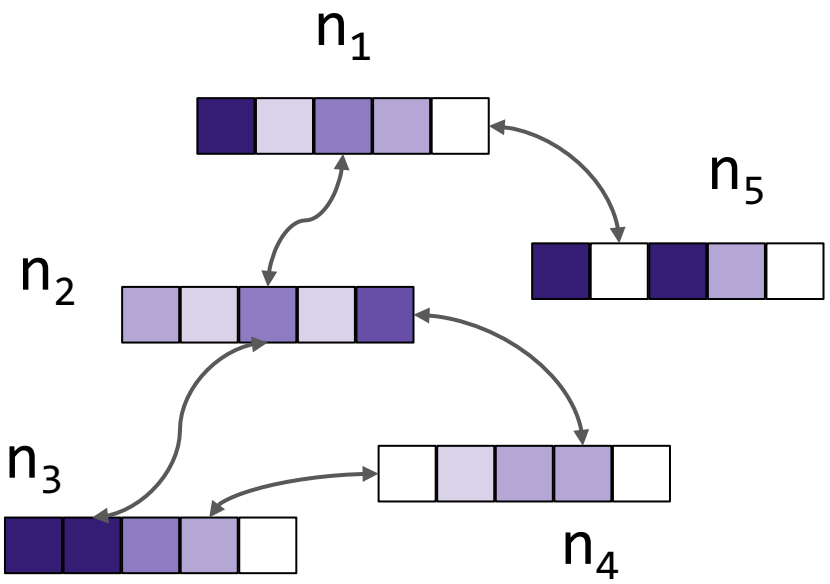


Step 2: Predicting Function Label



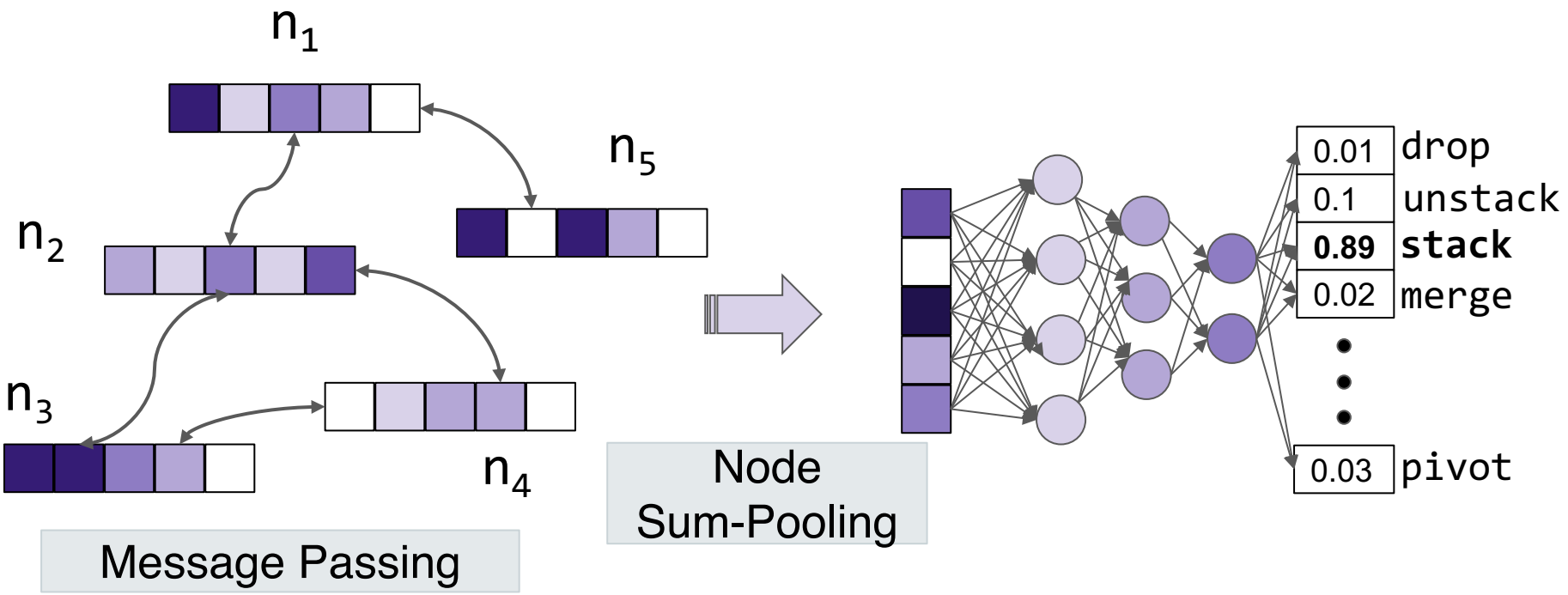
M. Allamanis, M. Brockschmidt, and M. Khademi. *Learning to represent programs with graphs*. ICLR 2018.

Graph Neural Network



Message Passing

Graph Neural Network



Training the Predictor

- Training set: 1,000,000 random *<input, output, function>* tuples
- Validation set: 100,000 random *<input, output, function>* tuples
- Test set: 29 real-world examples (StackOverflow, pandas book)

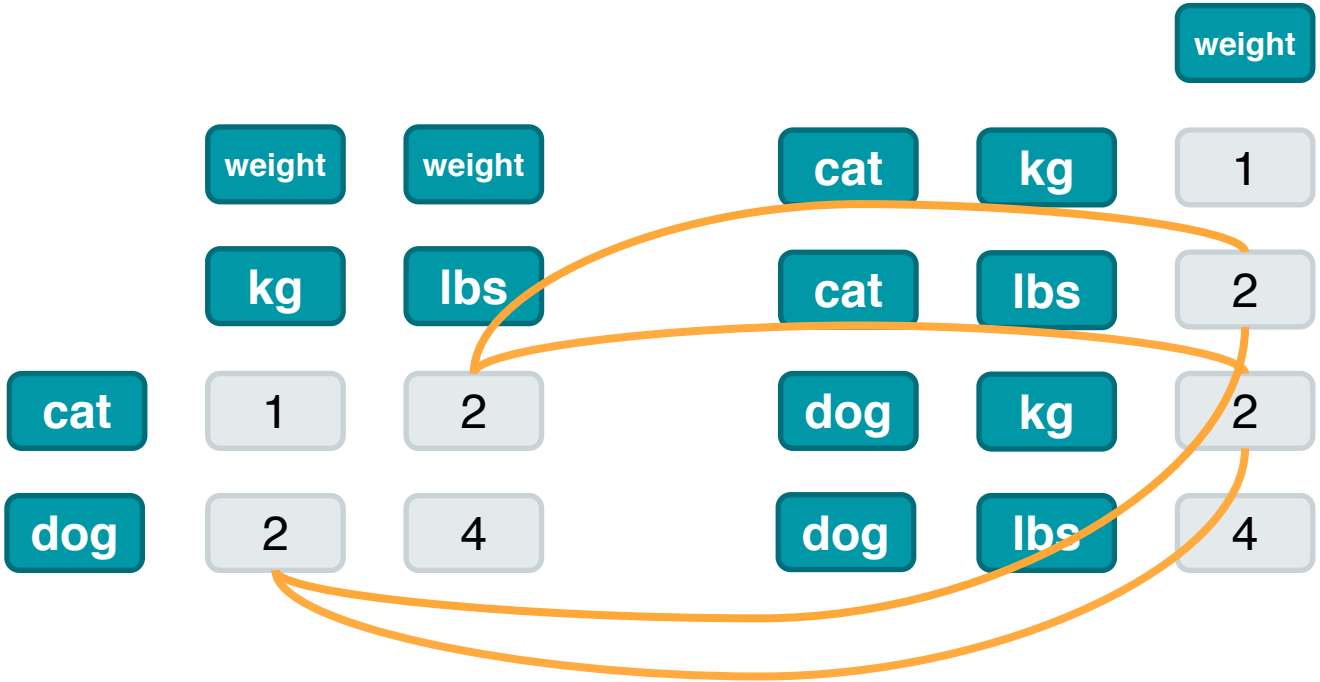
Accuracy Results

	Ground-Truth	
Suite	Top-1	Top-5
Validation	65%	94%
Test	59%	83%

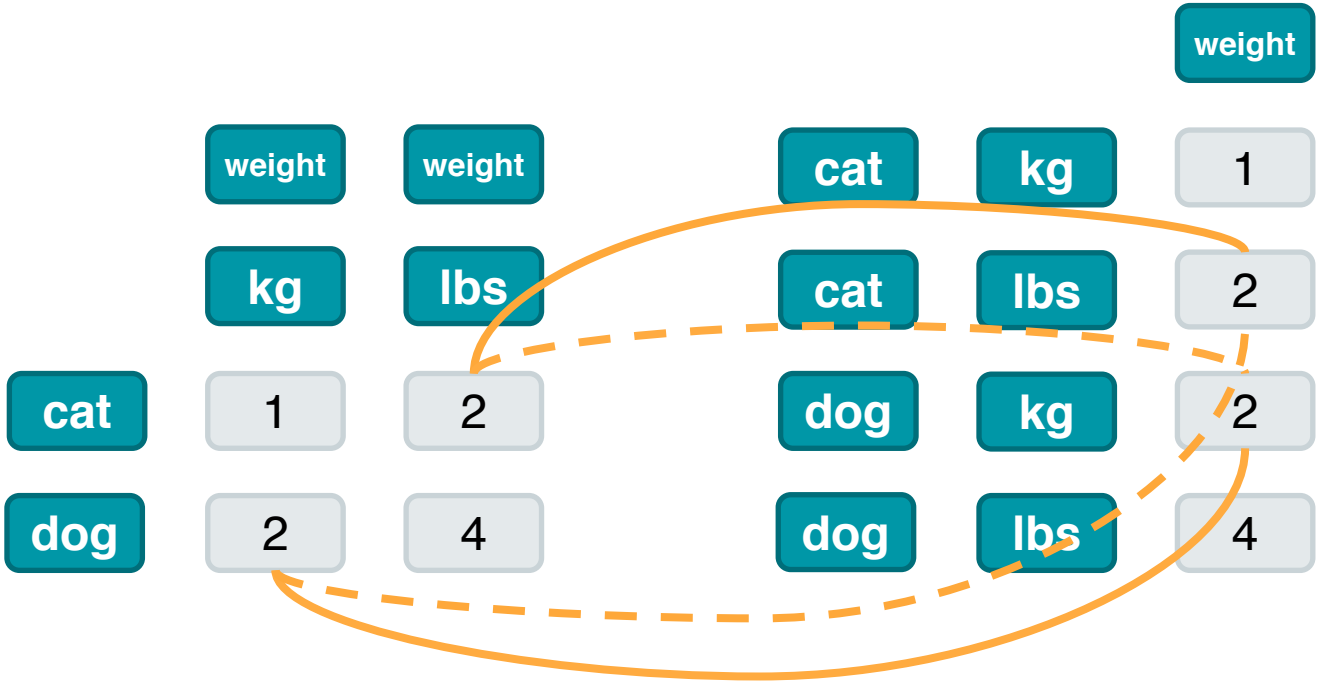
Accuracy Results

	Ground-Truth		Success-Rate	
Suite	Top-1	Top-5	Top-1	Top-5
Validation	65%	94%	82%	97%
Test	59%	83%	69%	83%

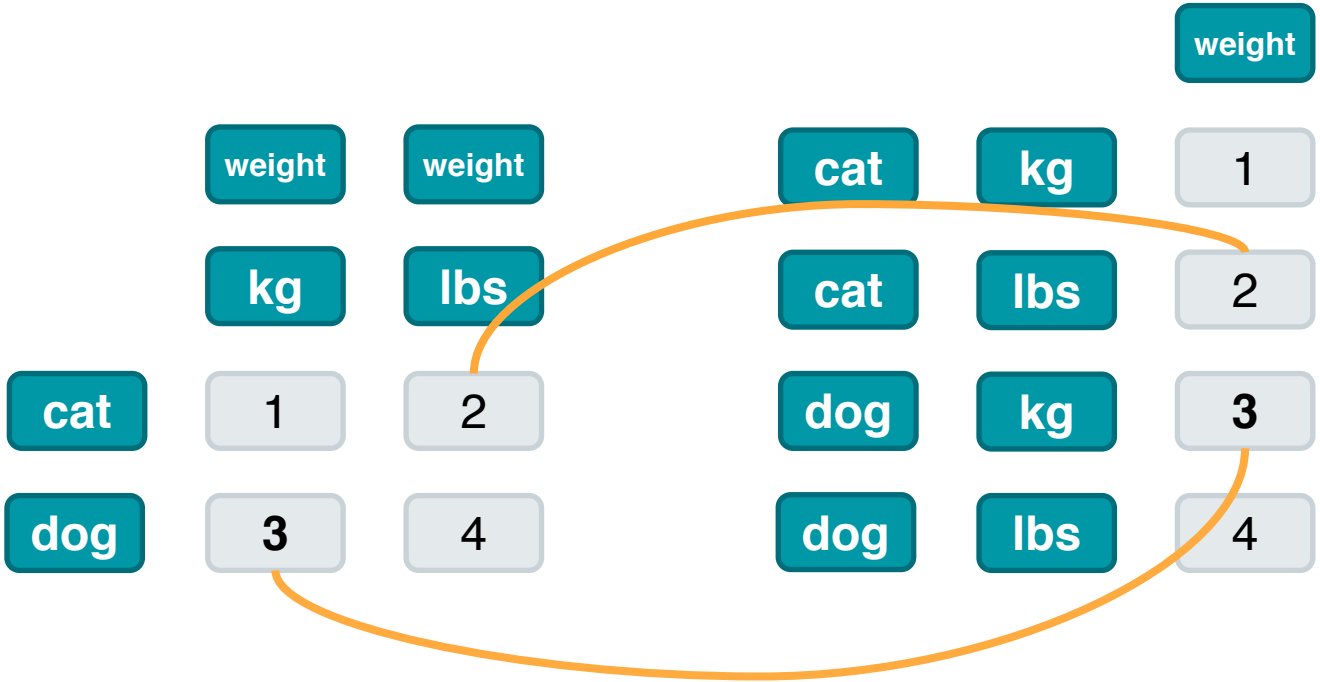
Cleaning: Removing Spurious Edges



Cleaning: Removing Spurious Edges



Cleaning: Removing Spurious Edges

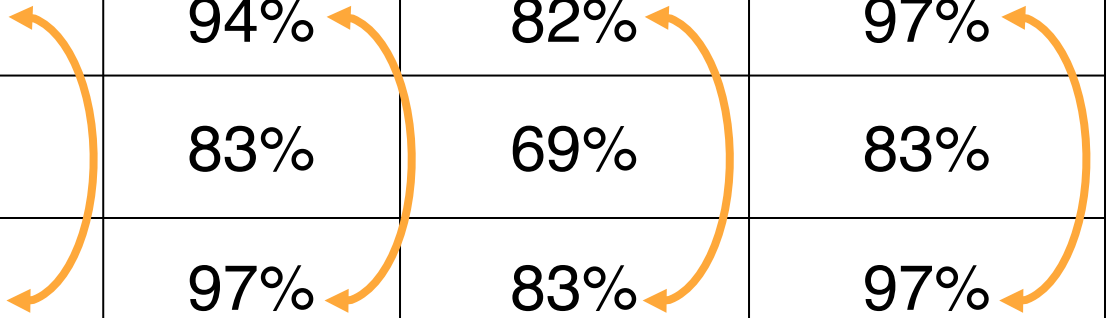


Accuracy Results

	Ground-Truth		Success-Rate	
Suite	Top-1	Top-5	Top-1	Top-5
Validation	65%	94%	82%	97%
Test	59%	83%	69%	83%
Cleaned Test	66%	97%	83%	97%

Accuracy Results

	Ground-Truth		Success-Rate	
Suite	Top-1	Top-5	Top-1	Top-5
Validation	65%	94%	82%	97%
Test	59%	83%	69%	83%
Cleaned Test	66%	97%	83%	97%



Moving Forward: Key Challenges

1. Accurately representing relationships (e.g. no spurious)
2. Semantically identical programs
3. Higher depths: sensible program generation

Moving Forward: Key Challenges

1. Accurately representing relationships (e.g. no spurious)
2. Semantically identical programs
3. Higher depths: sensible program generation

	Depth-2 Ground Truth		
Suite	Top-1	Top-5	Top-25
Validation	16.8%	43.5%	75.8%

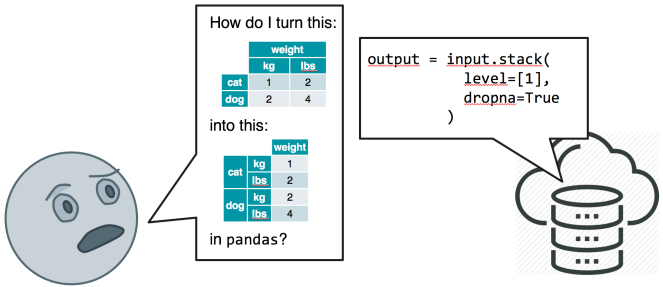
Moving Forward: Key Challenges

1. Accurately representing relationships (e.g. no spurious)
2. Semantically identical programs
3. Higher depths: sensible program generation

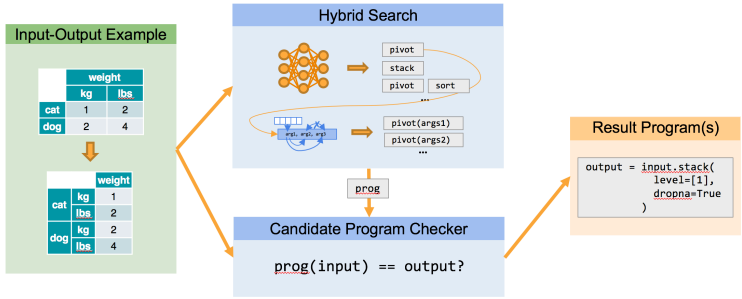
	Depth-2 Ground Truth		
Suite	Top-1	Top-5	Top-25
Validation	16.8%	43.5%	75.8%

```
v0 = input.stack()
v1 = input.eq(v0)
```

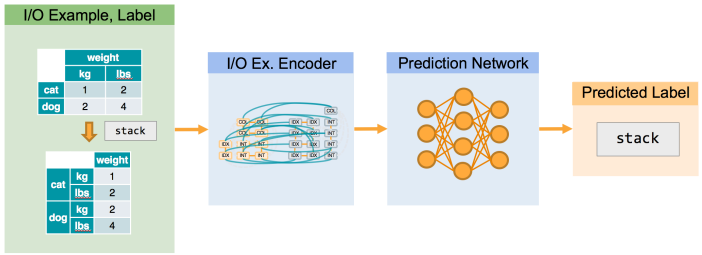
Our Goal: Automate *StackOverflow* for APIs



AutoPandas Technique



Zoom in: Neural Prediction Problem (Depth 1)



Accuracy Results

	Ground-Truth		Success-Rate	
Suite	Top-1	Top-5	Top-1	Top-5
Validation	65%	94%	82%	97%
Test	59%	83%	69%	83%
Cleaned Test	66%	97%	83%	97%

Caroline Lemieux, clemieux@berkeley.edu