

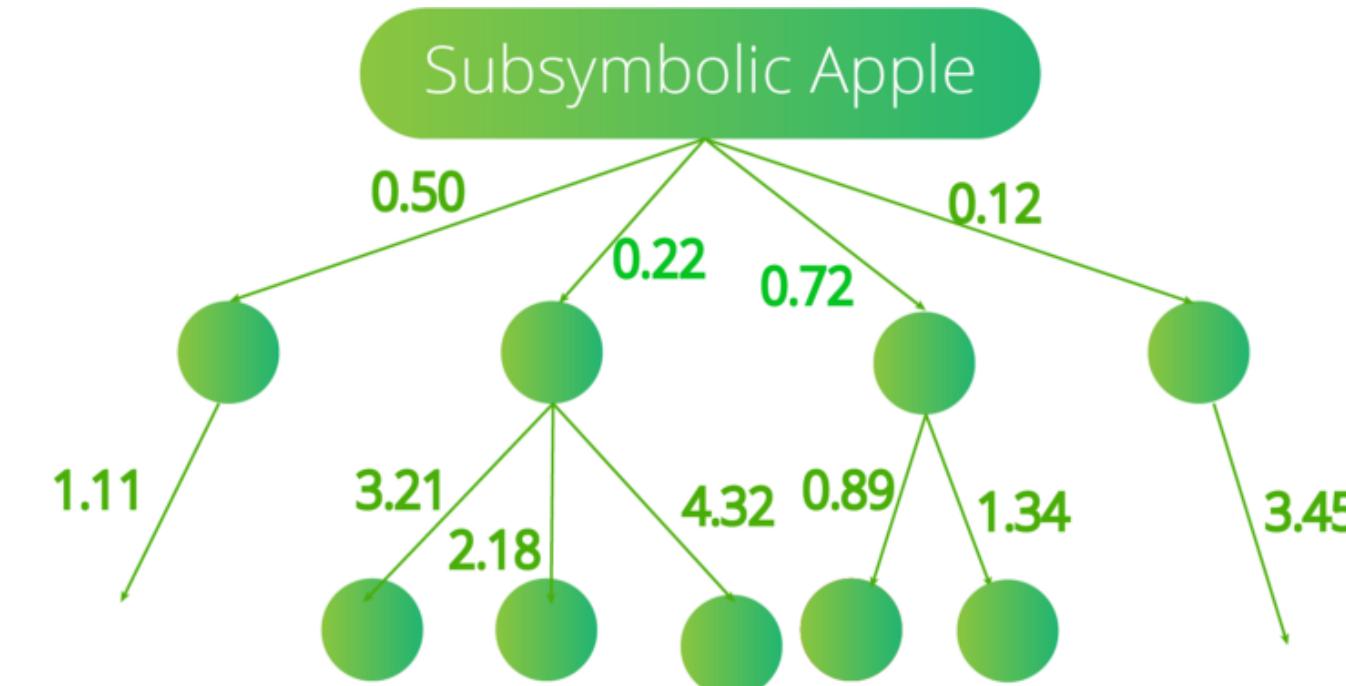
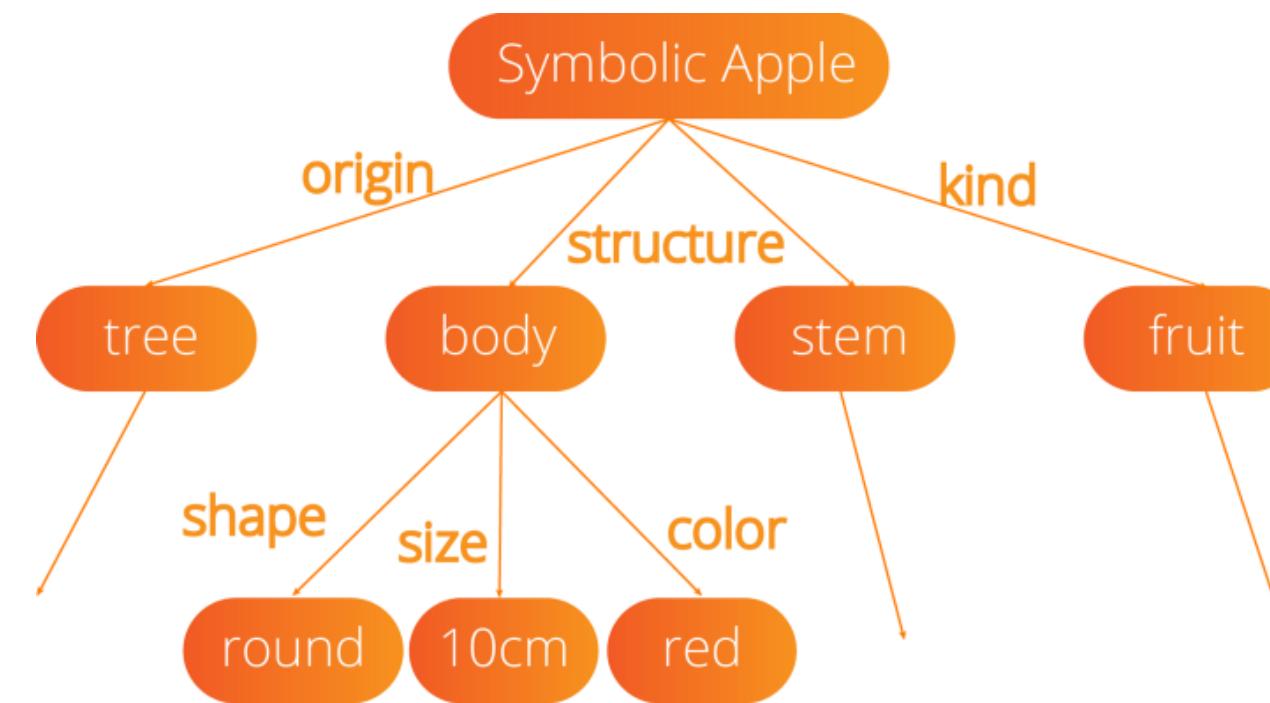
Program Reasoning

16. Program Synthesis as AI

Kihong Heo

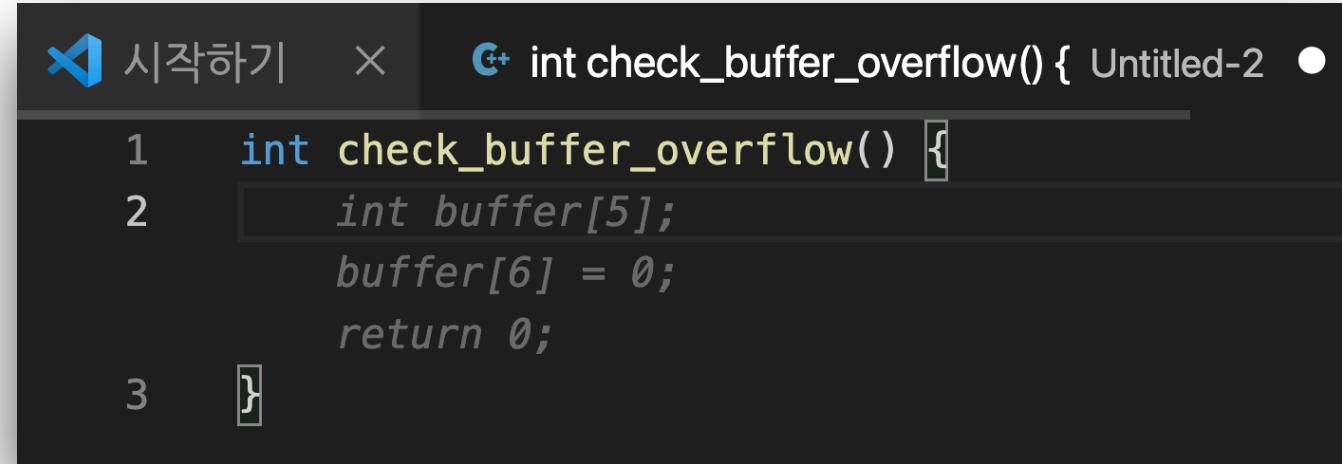


Two Major Camps of AI



- Symbolist
- 1950s - 1980s
- High-level symbolic representation
- Human-readable & interpretable
- Logic- & search- based
- Connectionist
- 1980s - present
- Low-level neural representation
- Efficient learning
- Differentiation-based

State of the Art



```
시작하기  ×  C+ int check_buffer_overflow() { Untitled-2 •  
1  int check_buffer_overflow() {  
2      int buffer[5];  
3      buffer[6] = 0;  
4      return 0;  
5  }
```

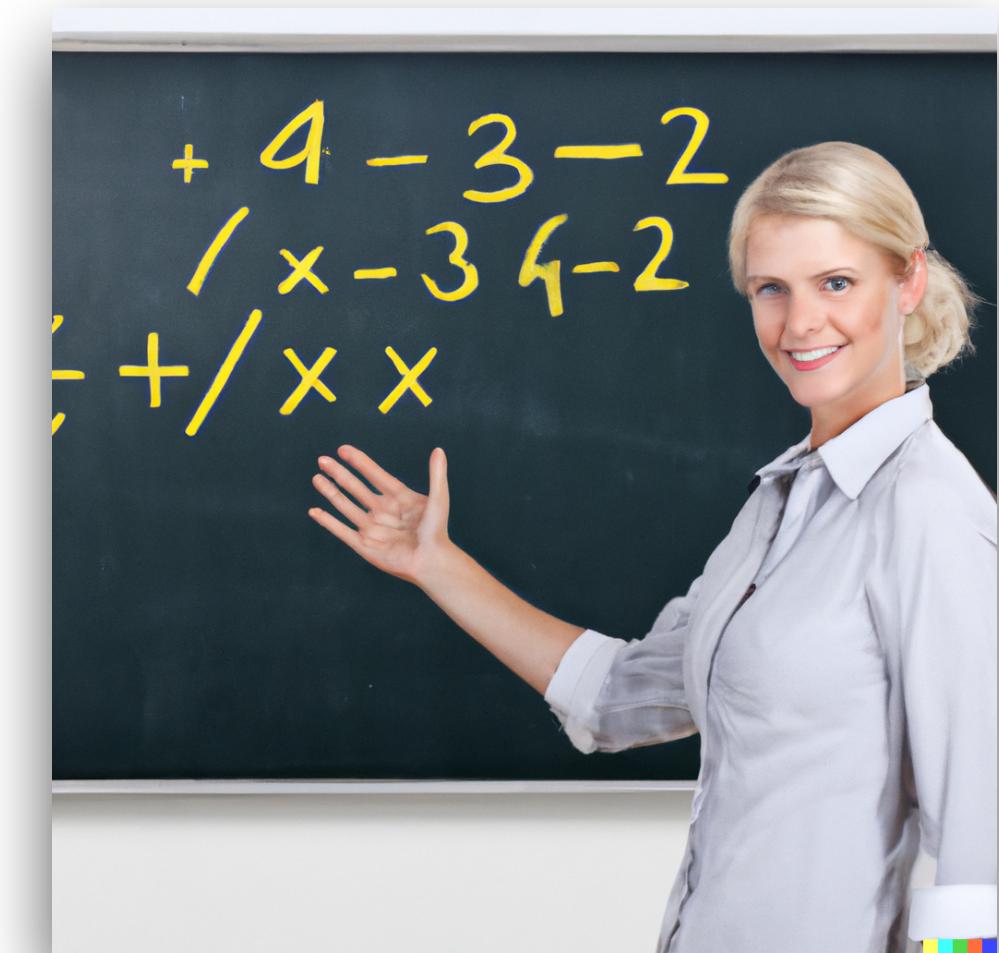
by Copilot

```
1 // read an image file  
2 int read_file() {  
3     FILE *fp;  
4     int i, j, k;  
5     int n;  
6     int m;  
7     int nc;  
8     int nr;  
9     int nb;  
10    int nc_max;  
11    int nr_max;  
12    int nb_max;  
13    int nc_min;  
14    int nr_min;  
15    int nb_min;  
16    int nc_avg;  
17    int nr_avg;  
18    int nb_avg;  
19    int nc_sum;  
20    int nr_sum;  
21    int nb_sum;  
22    int nc_var;  
23    int nr_var;  
24    int nb_var;  
25    int nc_std;  
26    int nr_std;  
27    int nb_std;  
28    int nc_med;  
29    int nr_med;  
30    int nb_med;  
31    int nc_mode;  
32    int nr_mode;  
33    int nb_mode;  
34    int nc_min_index;  
35    int nr_min_index;  
36    int nb_min_index;  
37    int nc_max_index;  
38    int nr_max_index;  
39    int nb_max_index;  
40    int nc_med_index;  
41    int nr_med_index;  
42    int nb_med_index;  
43    int nc_mode_index;  
44    int nr_mode_index;  
45    int nb_mode_index;  
46    int nc_sum_index;  
47    int nr_sum_index;  
48    int nb_sum_index;  
49    int nc_var_index;  
50    int nr_var_index;  
51    int nb_var_index;  
52    int nc_std_index;  
53    int nr_std_index;  
54    int nb_std_index;  
55    int nc_avg_index;  
56    int nr_avg_index;  
57    int nb_avg_index;  
58    int nc_min_index_index;  
59    int nr_min_index_index;
```

by Copilot



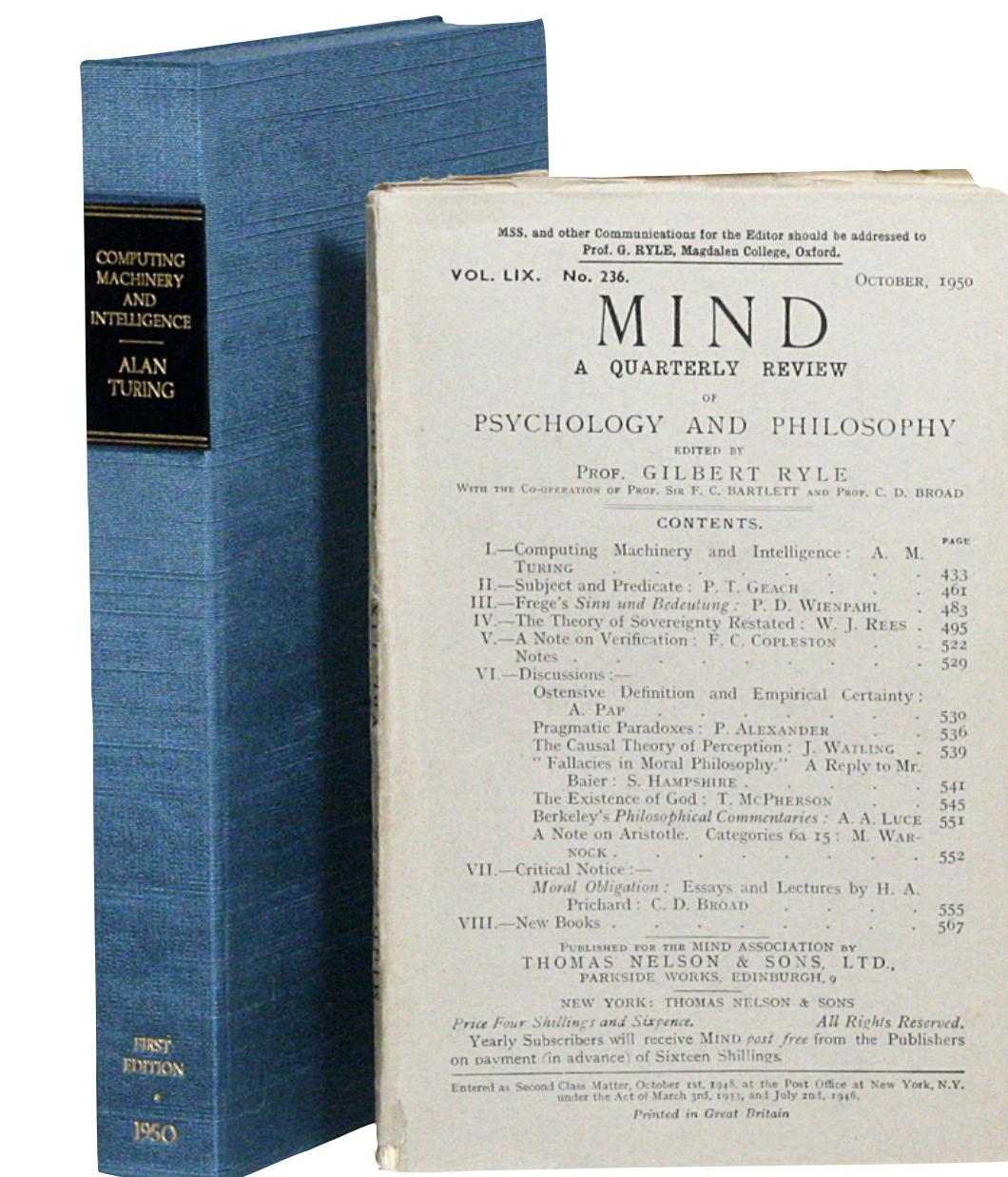
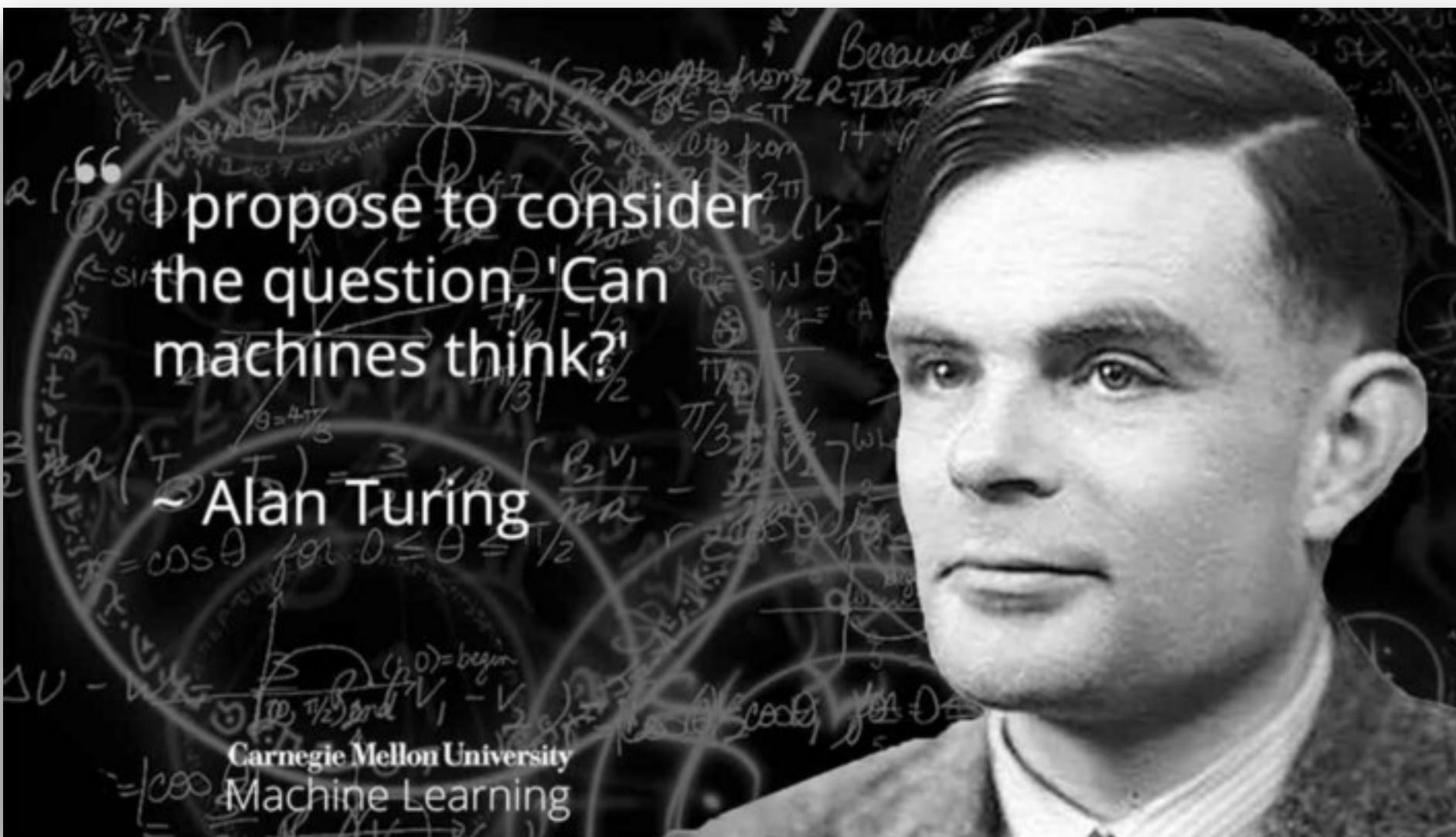
by Dall-E



by Dall-E

Program Synthesis as Symbolic AI

- Turing's dream
- Program: explainable & executable & verifiable



Inductive Logic Programming (ILP)

- A subfield of symbolic artificial intelligence
- Goal: given a dataset (inductive), infer a set of rules (logic programming)
- Synthesizing programs in logic programming languages
 - E.g., Prolog, Datalog

Example

- Parent

Dataset

parent(a,b)	parent(a,c)	parent(d,b)
father(a,b)	father(a,c)	mother(d,b)
male(a)	female(c)	female(d)

Learned Rules

```
father(X,Y) :- parent(X,Y) & male(X)
mother(X,Y) :- parent(X,Y) & female(X)
```

- Transitive closure

Dataset

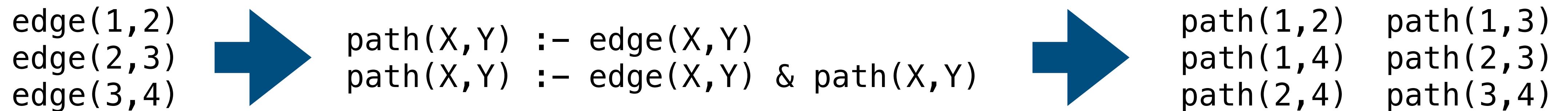
edge(1,2)	edge(2,3)	edge(3,4)
path(1,2)	path(1,3)	path(1,4)
path(2,3)	path(2,4)	path(3,4)

Learned Rules

```
path(X,Y) :- edge(X,Y)
path(X,Y) :- edge(X,Z) & path(Z,Y)
```

Datalog Programs

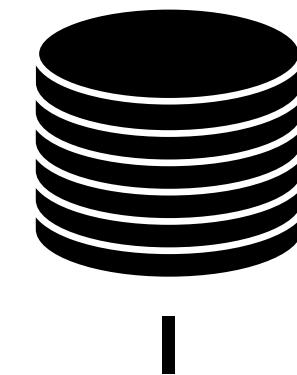
- A set of Horn clause rules ($X_1 \wedge X_2 \wedge \dots \wedge X_n \rightarrow H$)
- Input & output: a set of tuples
- Applications: big data analysis, network protocol, program analysis, etc



Datalog Program Synthesis

- Given a set of candidate rules, find a subset that is consistent with a given examples
 - A typical combinatorial optimization problem (i.e., NP-hard)
- In this lecture, we assume a set of candidates is predefined

edge(1,2)
edge(2,3)
edge(3,4)

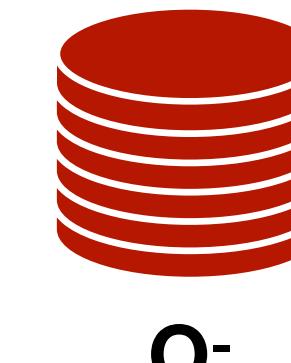


✓ path(x,y) :- edge(x,y).
✗ path(x,x) :- edge(x,y).
✓ path(x,z) :- edge(x,y), path(y,z).
✗ path(x,y) :- path(y,x).

...



path(1,2) path(1,3)
path(1,4) path(2,3)
path(2,4) path(3,4)



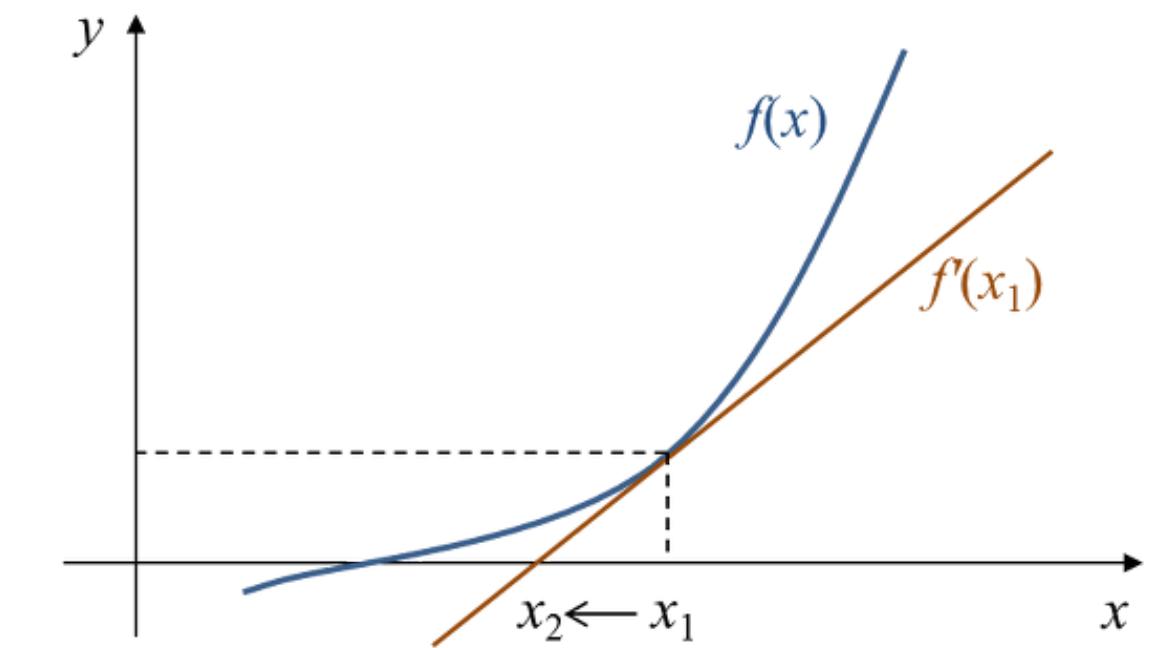
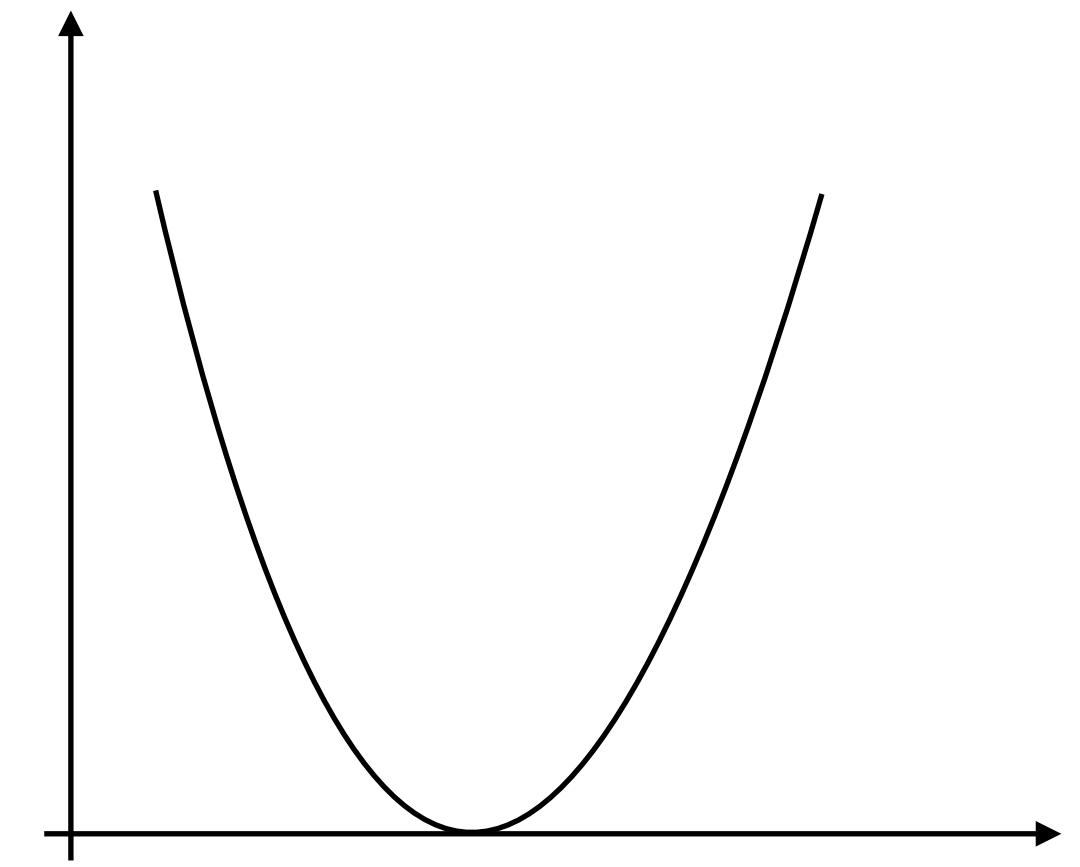
path(2,1) path(3,1)
path(4,1) path(4,2)

Challenges

- Huge search space
 - E.g., # of possible combinations of 50 candidate rules?
- If a wrong rule is chosen? The program produces a wrong tuple
- If a correct rule is missed? The program does not produce a correct tuple
- That is, how to find a point where the “loss” is zero?
 - Loss: the amount of derived wrong tuples + underived correct tuples

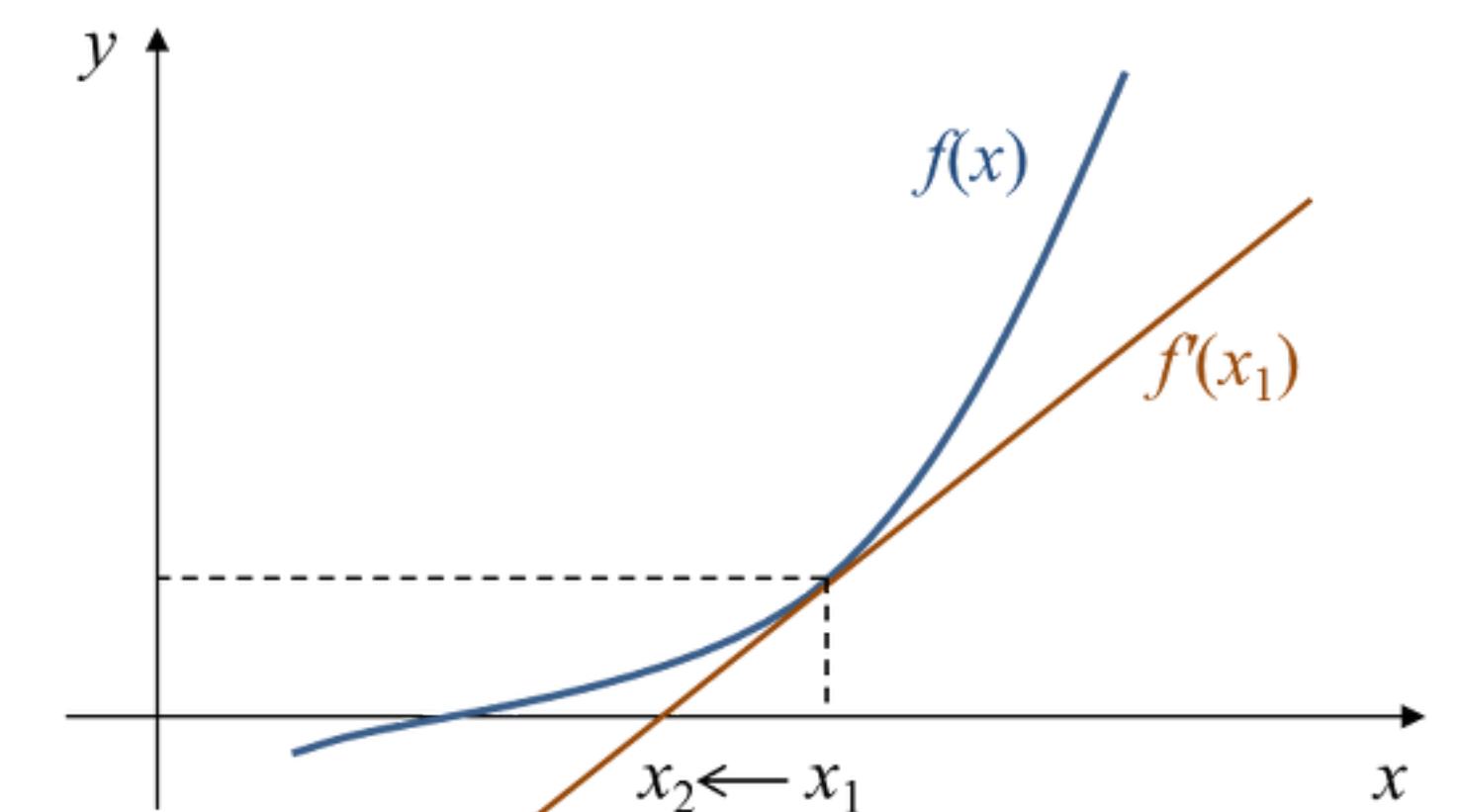
Analogy

- In other fields of mathematics, how to find a zero point?
- Enumerative approach: general but not efficient
 - E.g., 0, 1, 2, 3, 4...
- Algebraic approach: efficient but not general
 - E.g., $\frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$ for quadratic equation, but ≥ 5 -degree?
- Approximative approach: moderately efficient and general
 - E.g., Newton's method



A Solution: Difflog*

- A Datalog synthesis algorithm using numerical optimization
- Key idea: solving combinatorial optimization via numerical optimization
- Why numerical optimization? Many powerful algorithms exist!
 - E.g., Newton's method for differentiable loss functions
- Problem: Datalog programs are not differentiable



*Si et al., Synthesizing Datalog Programs using Numerical Relaxation, IJCAI 2019

Idea 1: Provenance

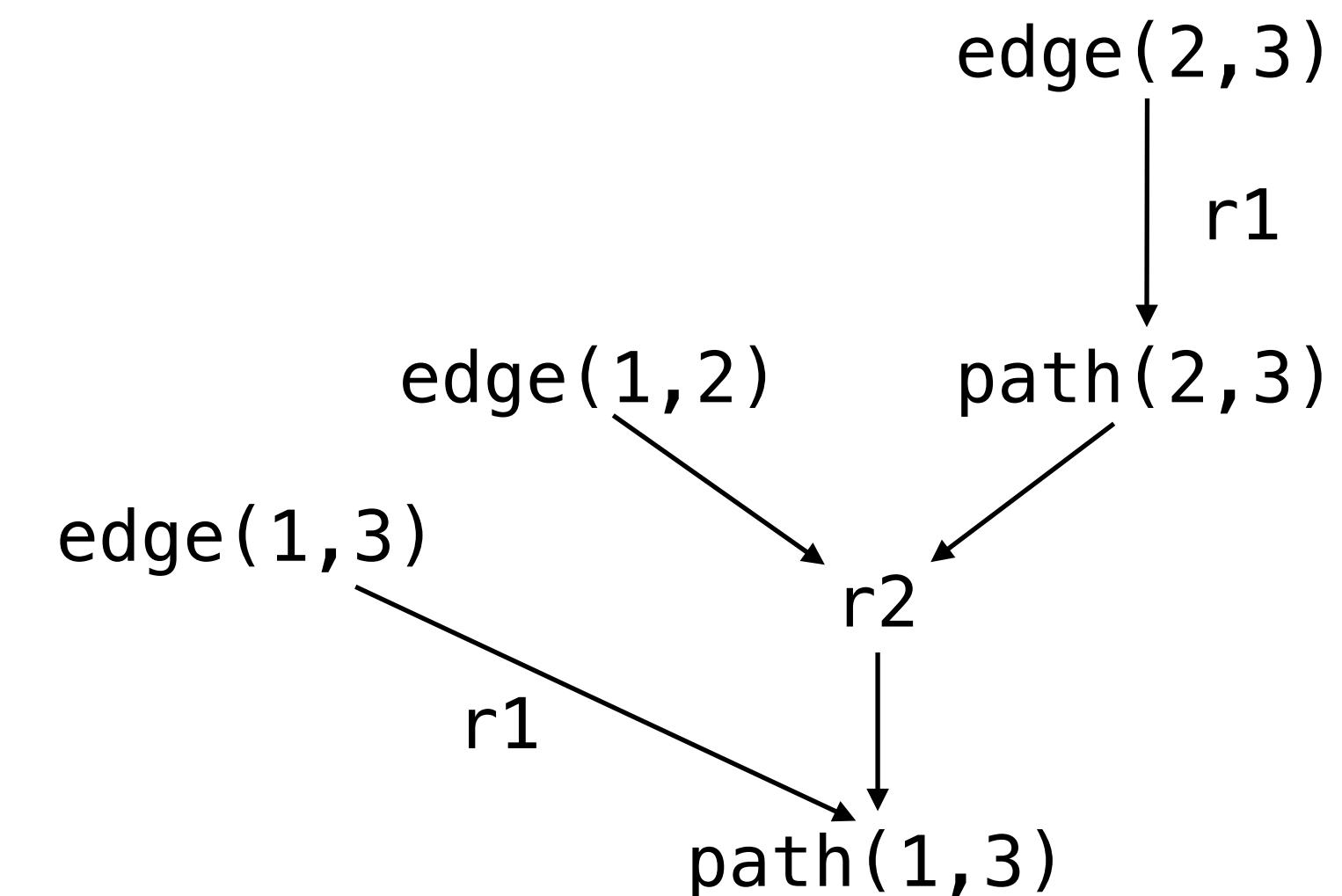
- Datalog programs produce provenance as well as output tuples
- Provenance: a proof that explains why a tuple is derived
 - If an undesired tuple is derived, we can see the reason

Rules

```
r1: path(x,y) :- edge(x,y).  
r2: path(x,z) :- edge(x,y), path(y,z).
```

Input tuples

```
{edge(1,2), edge(2,3), edge(1,3)}
```



Idea 2: Continuous Semantics (1)

- Interpret Datalog programs (non-continuous function) as continuous functions
 - Existence of tuple $\{0, 1\}$ to weight of tuple $[0, 1]$
 - Each rule is associated with a weight
 - The weight of a tuple is computed using the weights of rules on the provenance
- Then, combinatorial optimization problem → numerical optimization problem
 - Many existing algorithms applicable

Example (1)

Parameters: \vec{W}

```
0.7 path(x,y) :- edge(x,y).  
0.1 path(x,x) :- edge(x,y).  
0.9 path(x,z) :- edge(x,y), path(y,z).  
0.3 path(x,y) :- path(y,x).
```

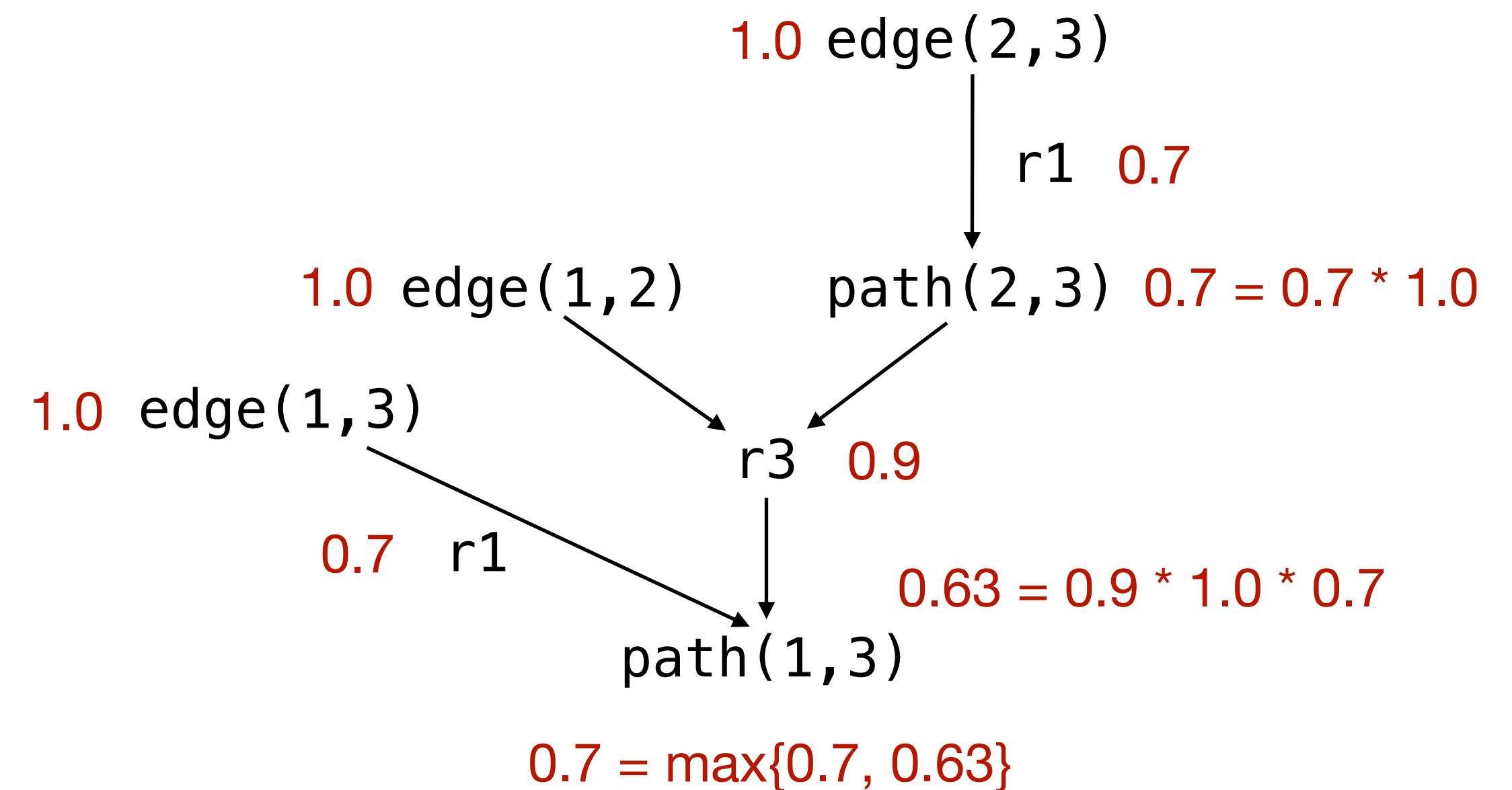
Input	edge(1,2)	edge(2,3)
Weight	1.0	1.0

Discrete semantics

$$v_t = \bigvee_g (v_{a_1} \wedge v_{a_2} \wedge \dots \wedge v_{a_k})$$

Continuous semantics

$$v_t = \max_g (w_g \times v_{a_1} \times v_{a_2} \times \dots \times v_{a_k})$$



Example (2)

Parameters: \vec{W}

```

0.7 path(x,y) :- edge(x,y).
0.1 path(x,x) :- edge(x,y).
0.9 path(x,z) :- edge(x,y), path(y,z).
0.3 path(x,y) :- path(y,x).

```

Input	edge(1,2)	edge(2,3)
Weight	1.0	1.0

Output	path(1,2)	path(2,3)	path(1,3)	path(1,1)	path(2,1)
Weight (v_t)	0.7	0.7	0.63	0.1	0.21
Expectation	1	1	1	0	0

Discrete semantics

$$v_t = \bigvee_g (v_{a_1} \wedge v_{a_2} \wedge \dots \wedge v_{a_k})$$

Continuous semantics

$$v_t = \max_g (w_g \times v_{a_1} \times v_{a_2} \times \dots \times v_{a_k})$$

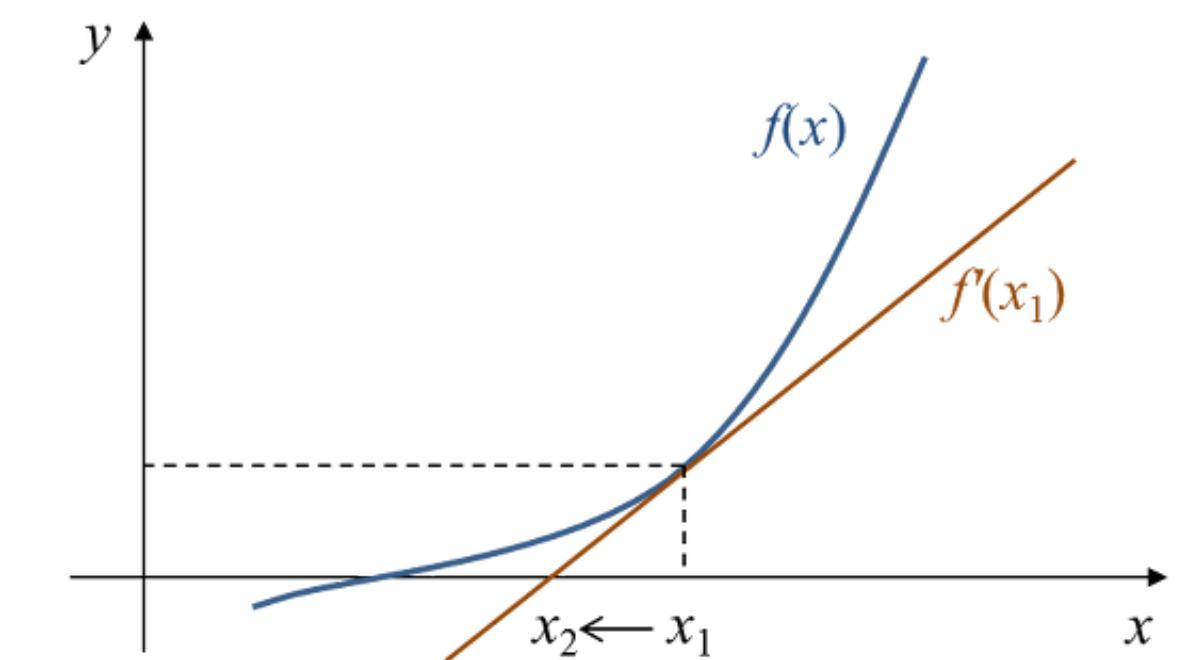
Optimization problem:
find \vec{W} that minimizes the following loss

$$\text{loss} = \sum_{t \in \text{pos}} (1 - v_t)^2 + \sum_{t \in \text{neg}} (0 - v_t)^2$$

Numerical Optimization

$$\text{loss} = \sum_{t \in pos} (1 - v_t)^2 + \sum_{t \in neg} (0 - v_t)^2$$

- In continuous semantics, v_t is a polynomial with w_r (differentiable)
- Then, the loss function is a polynomial with w_r (differentiable)
- Solve using a well-known algorithm (e.g., Newton's method)
 - loss is 0 = consistent with all the examples = a desired program



Summary

- Inductive logic programming (ILP): symbolic AI \cap program synthesis
- A long-standing argument in AI: connectionism vs symbolism
 - Connectionism (neural network): good at image recognition, machine translation, etc
 - Symbolism (logic): good at equation solving, logical reasoning, etc
- What is the future of AI (or programming)?
 - Neuro-symbolic AI: how to effectively combine both paradigms?