Inductive Programming
Lecture 3
One-shot induction and Bias reformulation

Stephen Muggleton
Department of Computing
Imperial College, London and
University of Nanjing

10th October, 2024

Papers for this lecture

Paper3.1: S.H. Muggleton, W-Z. Dai, C. Sammut, A. Tamaddoni-Nezhad, J. Wen, and Z-H. Zhou. Meta-interpretive learning from noisy images. Machine Learning, 107:1097-1118, 2018.

Paper3.2: D. Lin, E. Dechter, K. Ellis, J.B. Tenenbaum, and S.H. Muggleton. Bias reformulation for one-shot function induction. In Proceedings of the 23rd European Conference on Artificial Intelligence (ECAI 2014), pages 525-530.

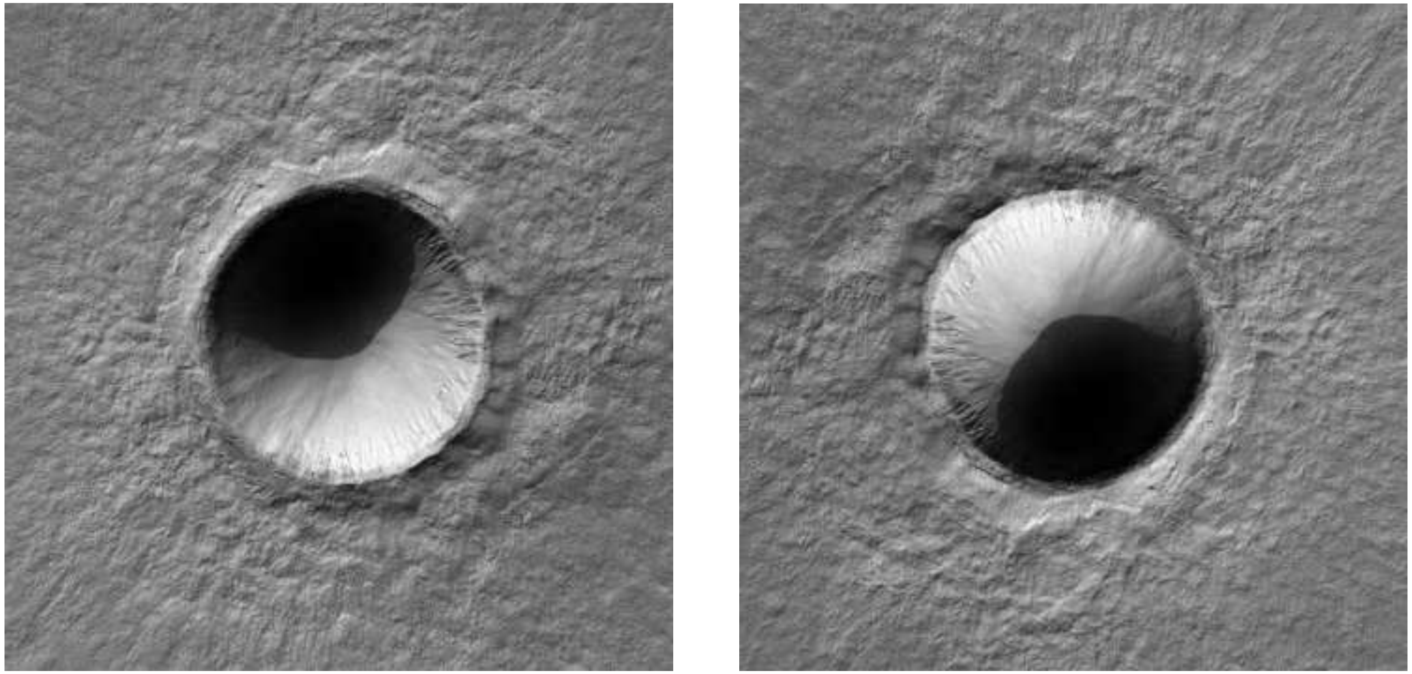
Motivation

- Inductive Programming
- Simple repetitive programs
- Human provides examples and checks results
- Requires data efficient inference
- PAC, Blumer bound, Strong Learning Bias
- Compatible with Human Bias? - Images and Text

Human versus Machine Learning

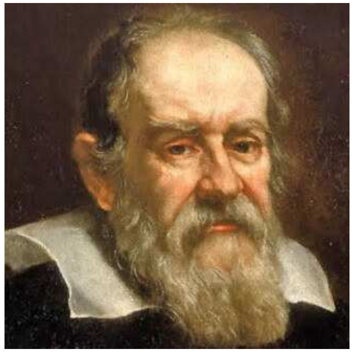
Characteristic	**Human**	**Statistical**
Examples per concept	Few (≈ 1) [Tenenbaum, 2011]	Many ($\geq 10K$)
Concepts to learn	Many ($\geq 10K$) [Brown et al, 2008]	Few (≈ 1)
Background knowledge	Large [Brown, 2000]	Small
Structure	Modular, re-useable [Omrod et al, 2004]	Monolithic

Human Visual Bias - Mars Crater/Mountain



(Credit: NASA/JPL/University of Arizona)

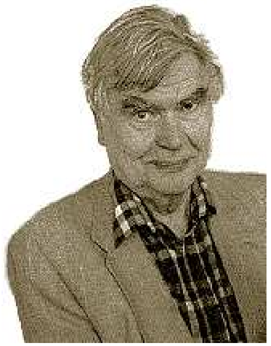
Logic, Learning and Vision



Galileo(1610)

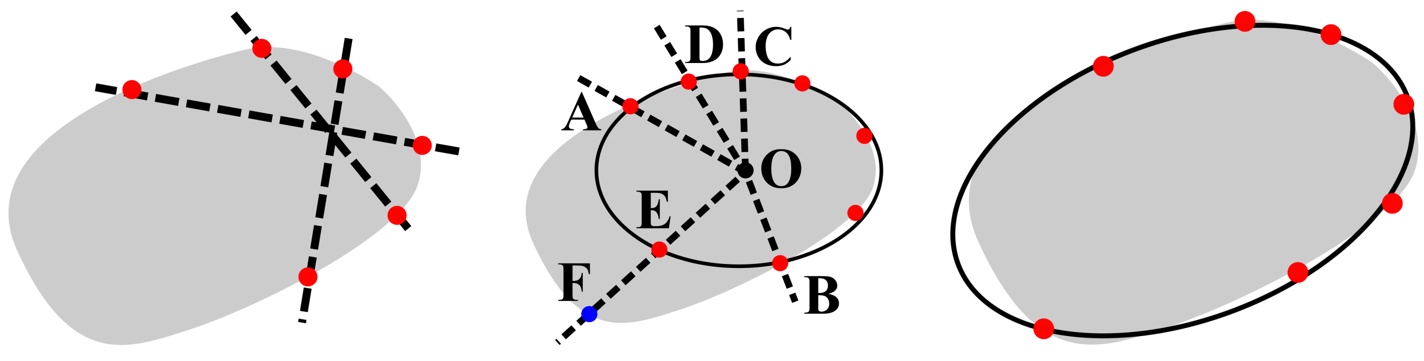
Helmholtz(1867)

Turing(1950)

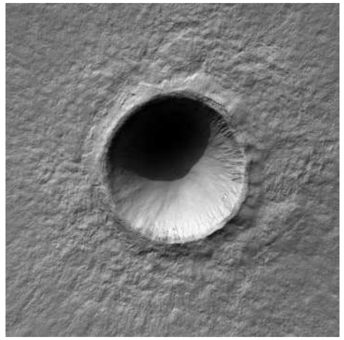


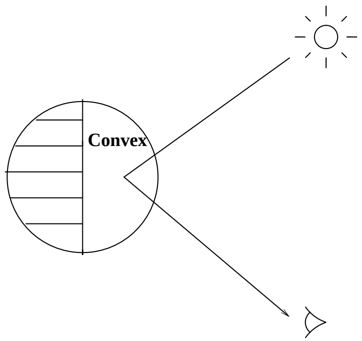
Gregory(1966)

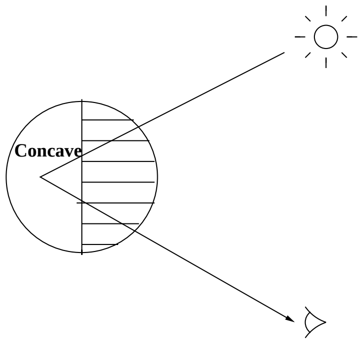
Low-level object detection - elipse model



High-level Visual Bias and Background Knowledge

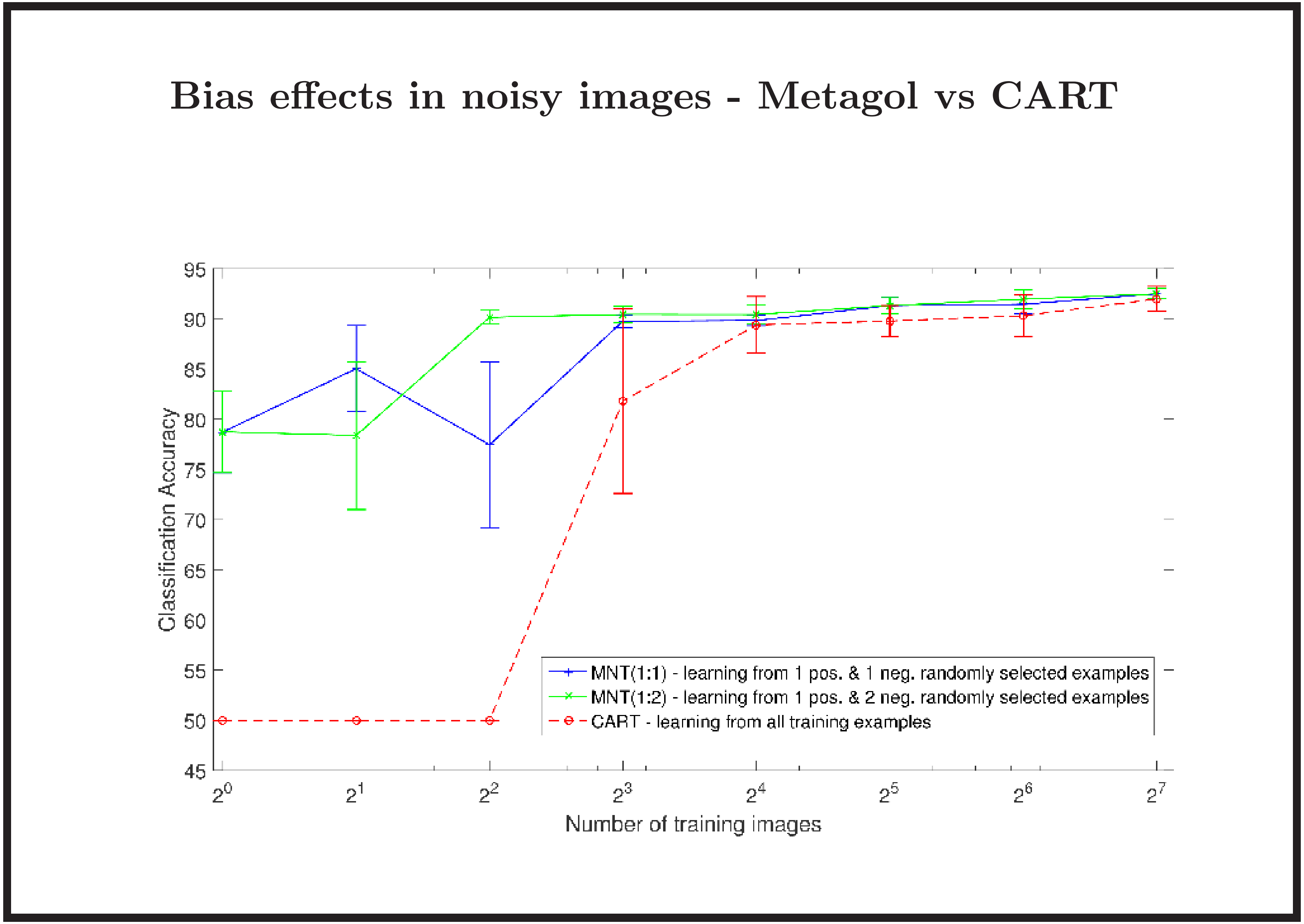






$$light(X, X).$$

$$light(X, Y) :- reflect(X, Z), light(Z, Y).$$


Bias effects in noisy images - Metagol vs CART
Classification Accuracy
95
90
85
80
75
70
65
60
55
50
45
2^0
2^1
2^2
2^3
2^4
2^5
2^6
2^7
Number of training images
MNT(1:1) - learning from 1 pos. & 1 neg. randomly selected examples
MNT(1:2) - learning from 1 pos. & 2 neg. randomly selected examples
CART - learning from all training examples

Textual Bias

Analogy problem

bob	BOB
alice	?

Alternative 1

bob	BOB
alice	BOICE

Alternative 2

bob	BOB
alice	ALICE

Harder tasks

Task1	miKe dwIGHT	Mike Dwight
Task2	European Conference on Artificial Intelligence	ECAI
Task3	My name is John.	John

Question

How can this human text transformation bias be learned by a computer?

Option1: Hardcode bias as DSL [Gulwani 2011,2012]
FlashFill, Excel 2013

brent.harold@hotmail.com	Brent Harold
matthew.rosman@yahoo.com	
jim.james@fas.harvard.edu	
ruby.clinton@mit.edu	
josh.smith@gmail.com	

Option1: Hardcode the bias [Gulwani 2011,2012]
FlashFill, Excel 2013

brent.harold@hotmail.com	Brent Harold
matthew.rosman@yahoo.com	Matthew Rosman
jim.james@fas.harvard.edu	Jim James
ruby.clinton@mit.edu	Ruby Clinton
josh.smith@gmail.com	Josh Smith

Option1: Non-intuitive FlashFill error

IaN RoDny	Ian Rodny
StaNleY TRAVis	Itanley Rley travis

Option2: Learn bias using variant of Meta-Interpretive Learning (Paper3.2)

brent.harold@hotmail.com	Brent Harold

ep04(A,B) ← ep04_1(A,C), ep04_2(C,B).

ep04_1(A,B) ← ep04_3(A,C), ep04_4(C,B).

ep04_2(A,B) ← ep04_3(A,C), skiprest(C,B).

ep04_3(A,B) ← make_uppercase(A,C), copyword(C,B).

ep04_4(A,B) ← skip1(A,C), write_space(C,B).

Learning time = **9.3 seconds**

Sequential episodes

ep02	james	James.

ep04	brent.harold@hotmail.com	Brent Harold

ep02(A,B) ← ep02_1(A,C), write_dot(C,B).

ep02_1(A,B) ← make_upper(A,C), copyword(C,B).

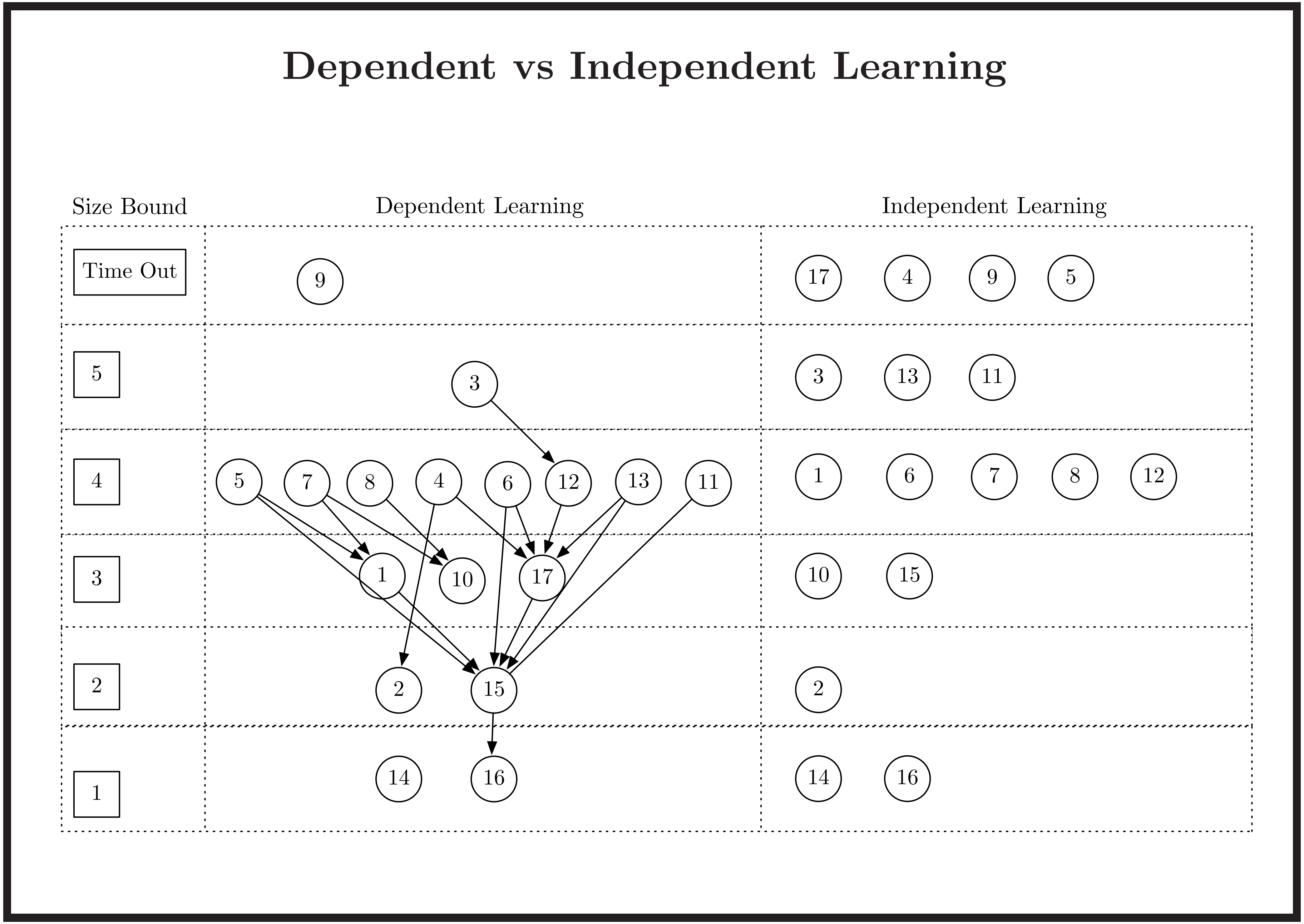
ep04(A,B) :- ep04_2(A,C), ep04_3(C,B).

ep04_2(A,B) :- ep04_4(A,C), skip1(C,B).

ep04_3(A,B) :- ep02_1(A,C), skiprest(C,B).

ep04_4(A,B) :- ep02_1(A,C), write_space(C,B).

Learning time = **3.1 seconds**



Dependent vs Independent Learning
Size Bound
Dependent Learning
Independent Learning
Time Out
5
4
3
2
1

Chain of programs from dependent learning

f_{03}(A,B) :- f_{12_1}(A,C), f_{12}(C,B).

f_{12}(A,B) :- f_{12_1}(A,C), f_{12_2}(C,B).

f_{12_1}(A,B) :- f_{12_2}(A,C), *skip*1(C,B).

f_{12_2}(A,B) :- f_{12_3}(A,C), *write*1(C,B,'.').

f_{12_3}(A,B) :- *copy*1(A,C), f_{17_1}(C,B).

f_{17}(A,B) :- f_{17_1}(A,C), f_{15}(C,B).

f_{17_1}(A,B) :- f_{15_1}(A,C), f_{17_1}(C,B).

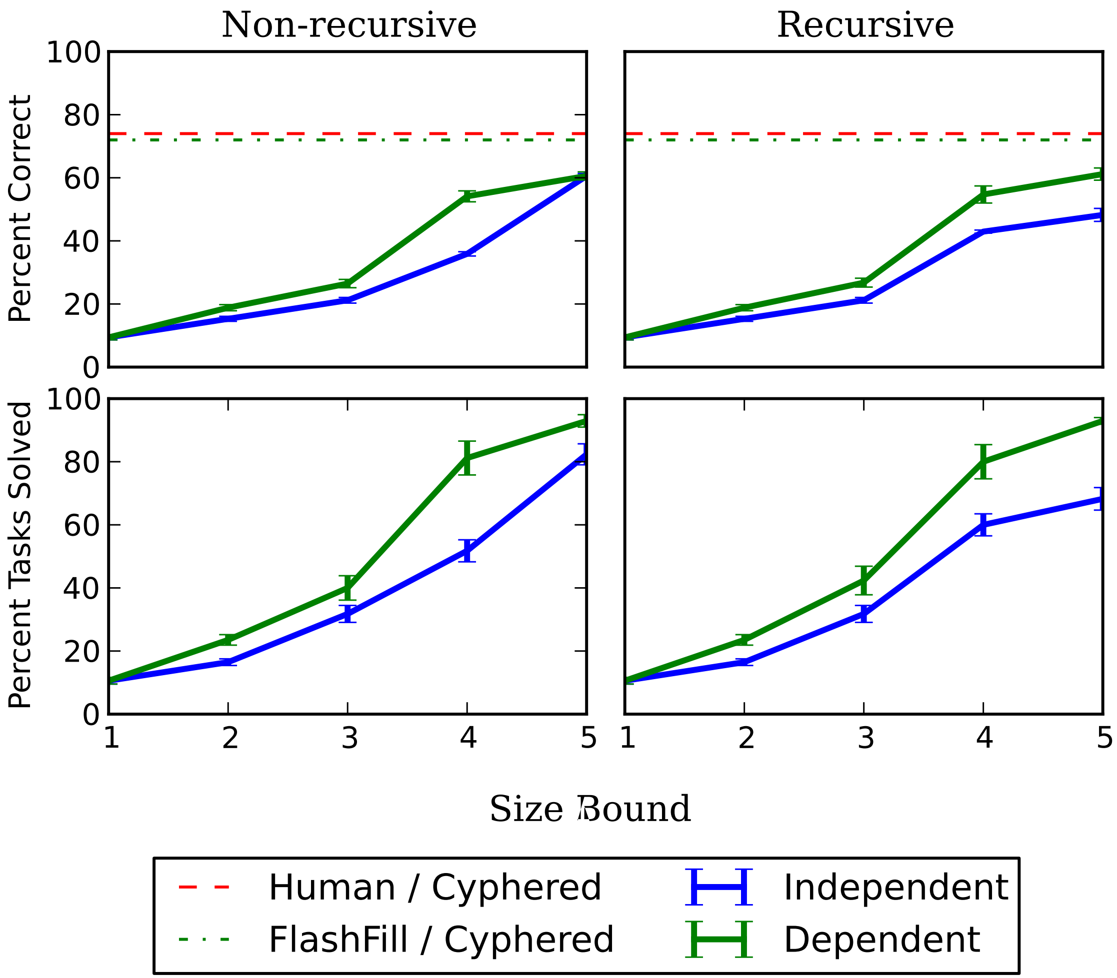
f_{17_1}(A,B) :- *skipalphanum*(A,B).

f_{15}(A,B) :- f_{15_1}(A,C), f_{16}(C,B).

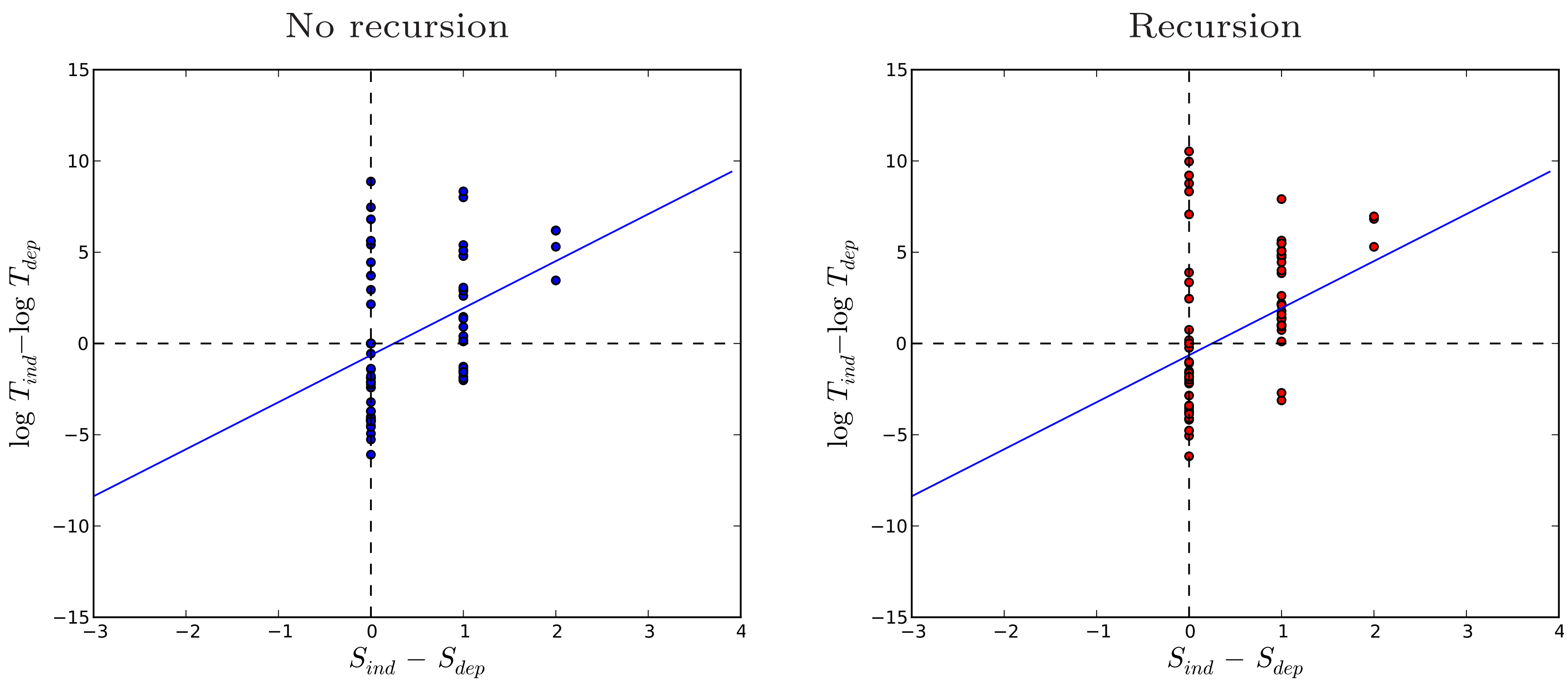
f_{15_1}(A,B) :- *skipalphanum*(A,C), *skip*1(C,B).

f_{16}(A,B) :- *copyalphanum*(A,C), *skiprest*(C,B).

Performance graphs



Running times Dependent vs Independent



Summary

- Human perceptual bias in Images and Text
- Bias can be learned by transfer in multi-task learning
- Effect is consistent increase in data and running efficiency
- Complex programs can be built by sharing invented predicates