Multitask Learning

Motivating Example

- 4 tasks defined on eight bits B_1-B_8:

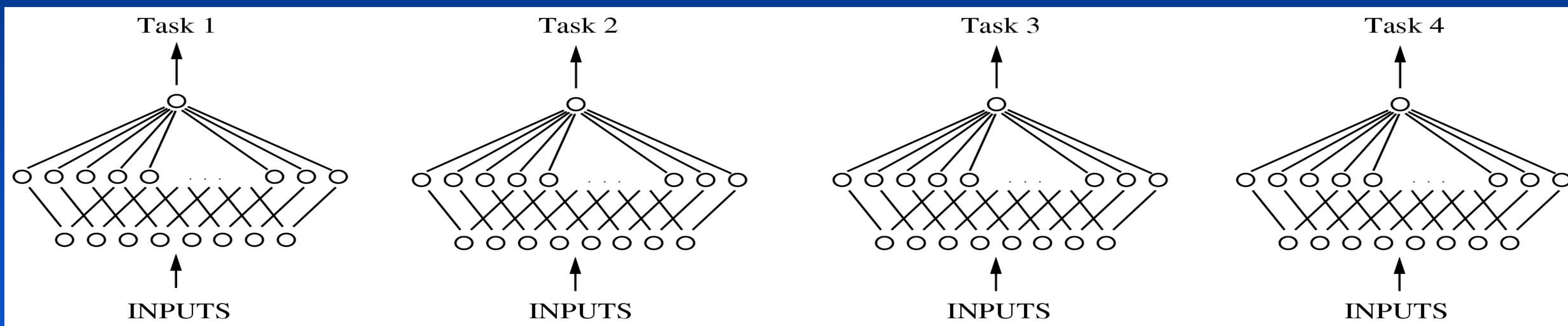
$$\text{Task 1} = \quad B_1 \quad \text{Parity}(B_2 \square B_6)$$

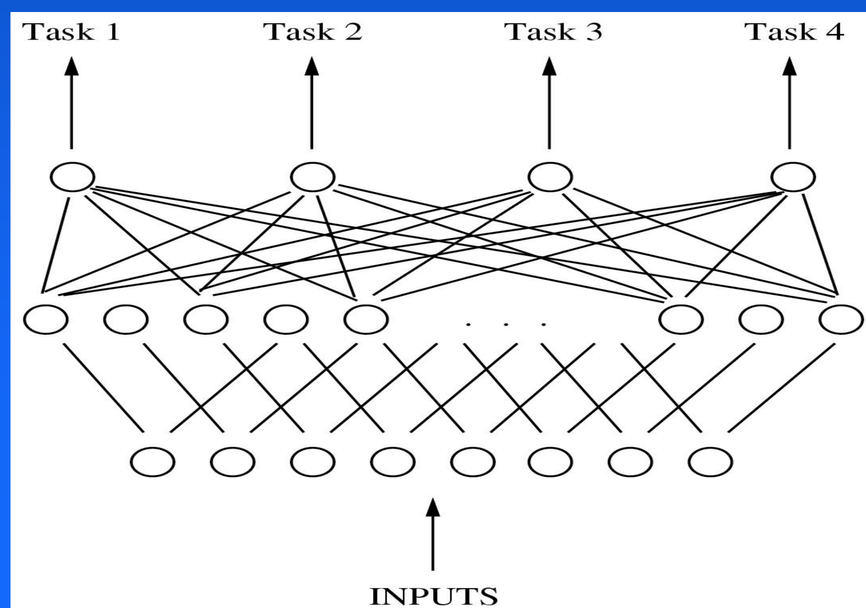
$$\text{Task 2} = \square B_1 \quad \text{Parity}(B_2 \square B_6)$$

$$\text{Task 3} = \quad B_1 \square \text{Parity}(B_2 \square B_6)$$

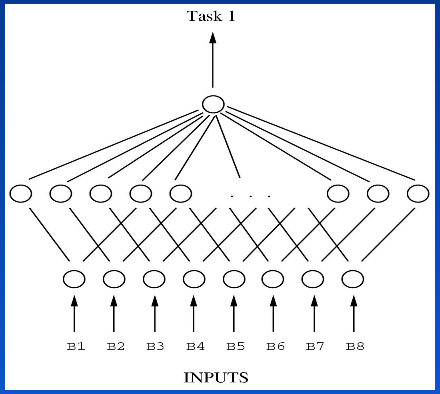
$$\text{Task 4} = \square B_1 \square \text{Parity}(B_2 \square B_6)$$

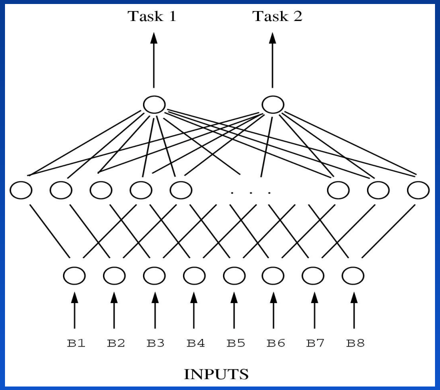
Motivating Example: STL & MTL

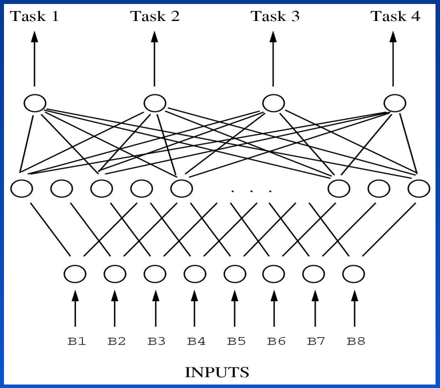


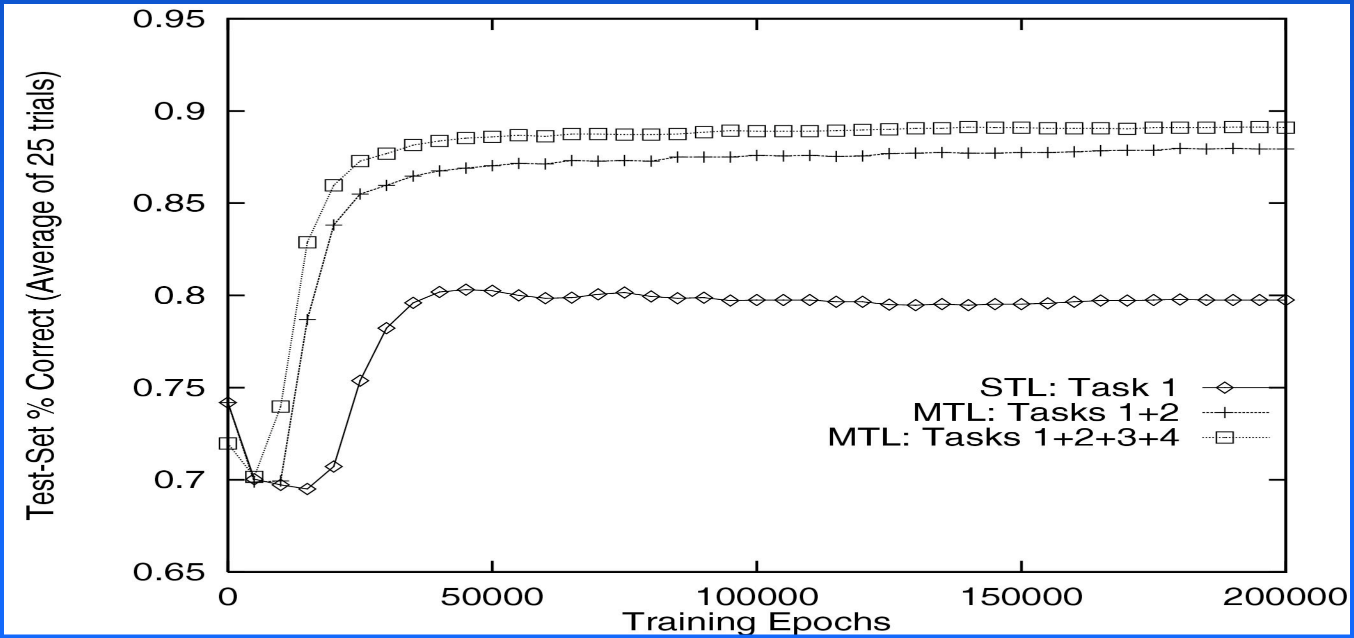


Motivating Example: Results







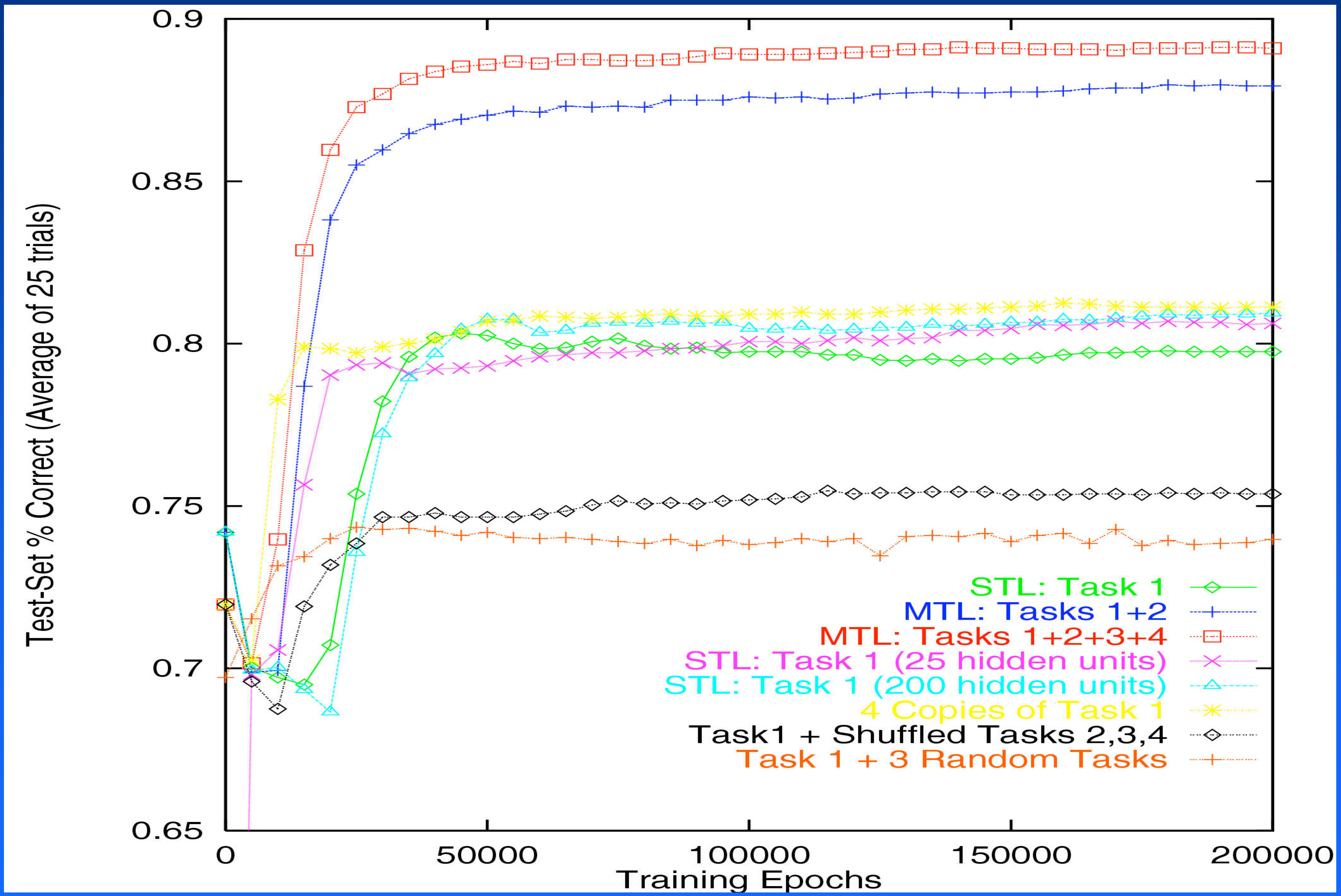


Motivating Example: Why?

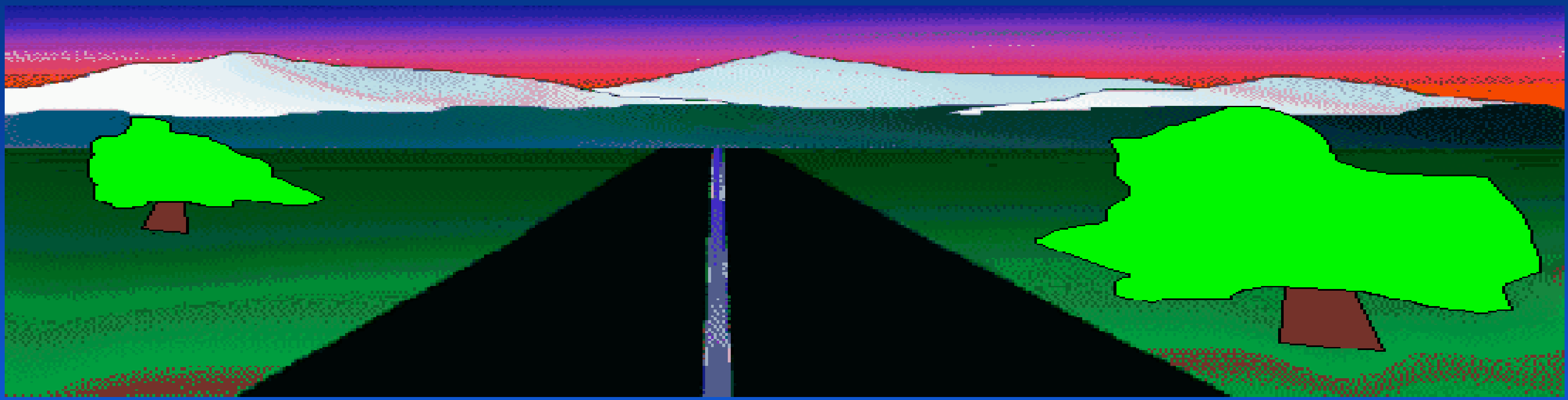
extra tasks:

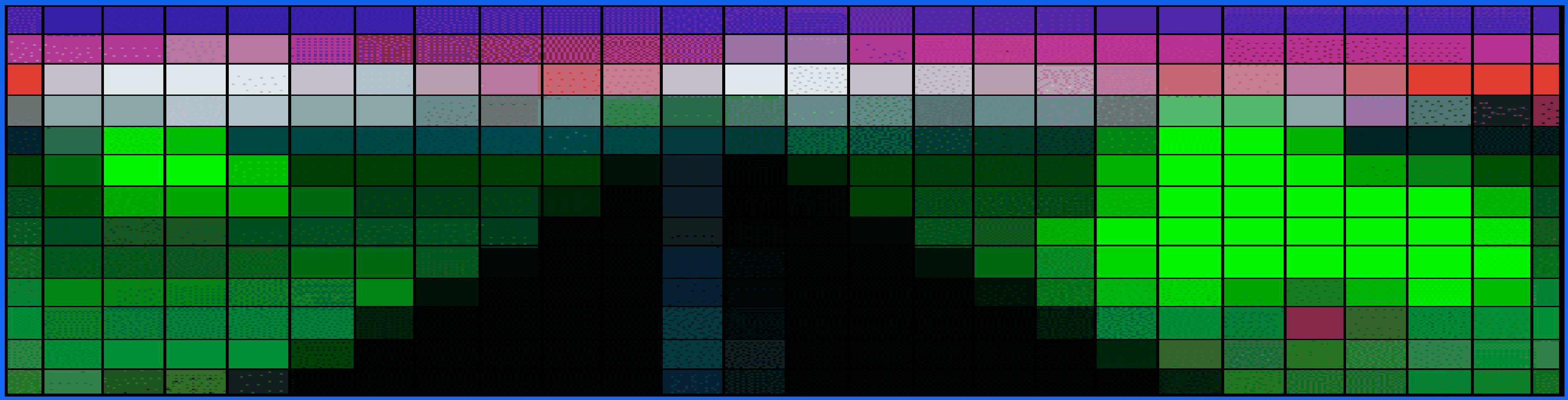
- add noise?
- change learning rate?
- reduce herd effect by differentiating hu's?
- use excess net capacity?
- . . . ?
- similarity to main task helps hidden layer learn better representation?

Motivating Example: Why?

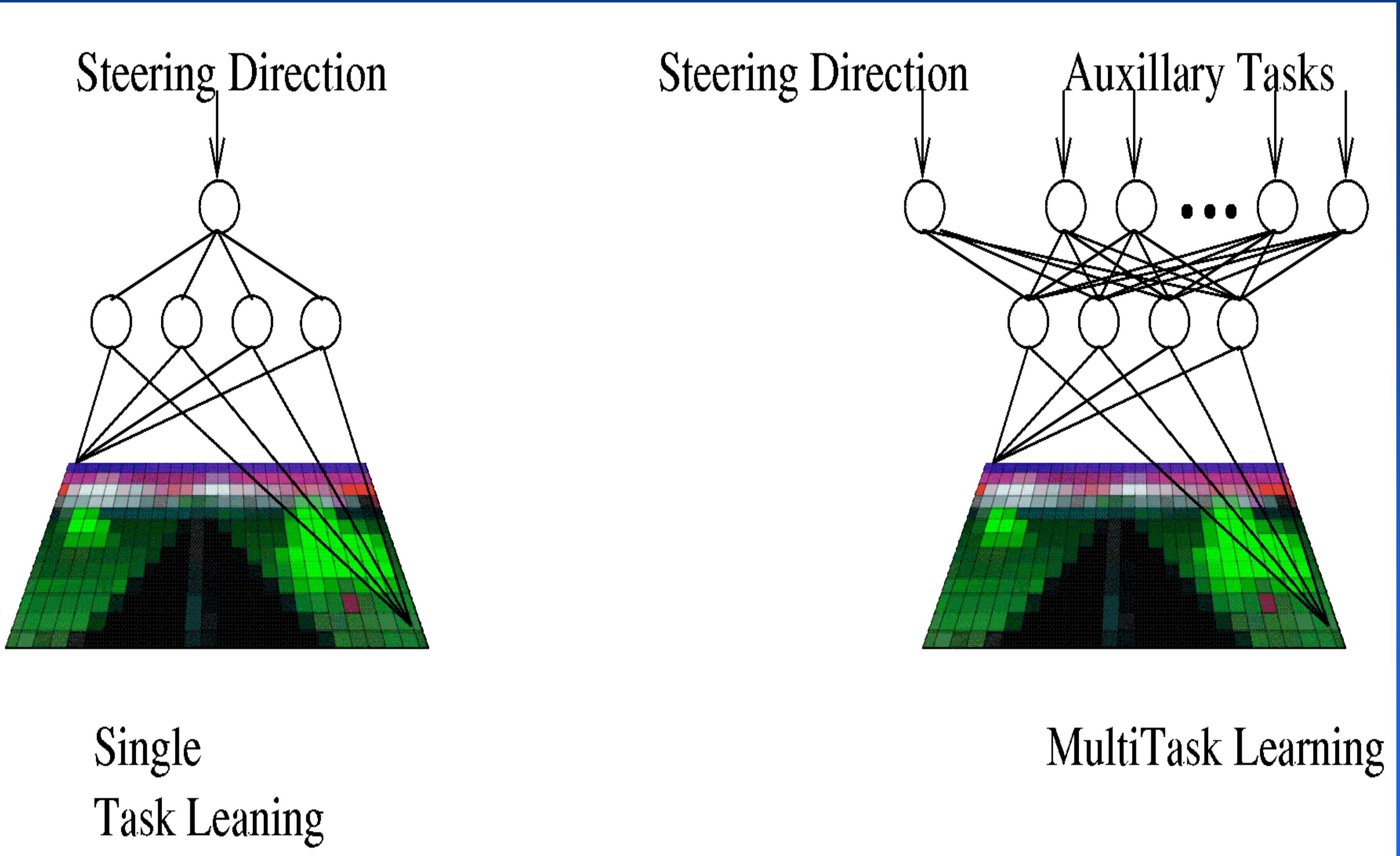


Autonomous Vehicle Navigation ANN

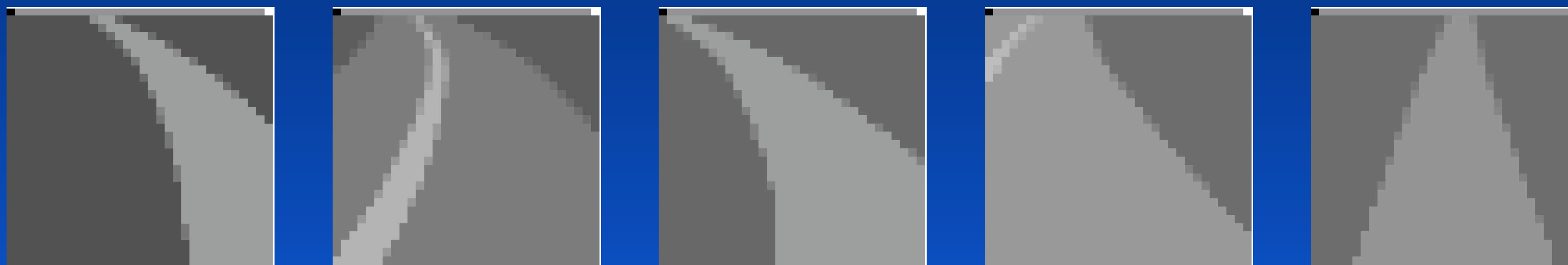




Multitask Learning for ALVINN



Problem 1: 1D-ALVINN



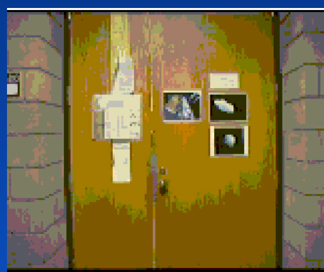
- simulator developed by Pomerleau
- main task: steering direction
- 8 extra tasks:
  - 1 or 2 lanes
  - horizontal location of centerline
  - horizontal location of road center, left edge, right edge
  - intensity of centerline, road surface, burms

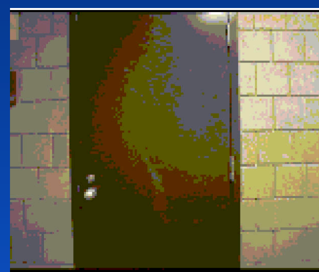
MTL vs. STL for ALVINN

TASK	STL 2hu	STL 4hu	STL 8hu	STL 16hu	MTL 16hu	%Change Best	%Change Average
1 or 2 Lanes	0.201	0.209	0.207	0.178	0.156	-12.40%	-21.50%
Left Edge	0.069	0.071	0.073	0.073	0.062	-10.10%	-13.30%
Right Edge	0.076	0.062	0.058	0.056	0.051	-8.90%	-19.00%
Line Center	0.153	0.152	0.152	0.152	0.151	-0.70%	-0.80%
Road Center	0.038	0.037	0.039	0.042	0.034	-8.10%	-12.80%
Road Greylevel	0.054	0.055	0.055	0.054	0.038	-29.60%	-30.30%
Edge Greylevel	0.037	0.038	0.039	0.038	0.038	2.70%	0.00%
Line Greylevel	0.054	0.054	0.054	0.054	0.054	0.00%	0.00%
Steering	0.093	0.069	0.087	0.072	0.058	-15.90%	-27.70%

Problem 2: 1D-Doors







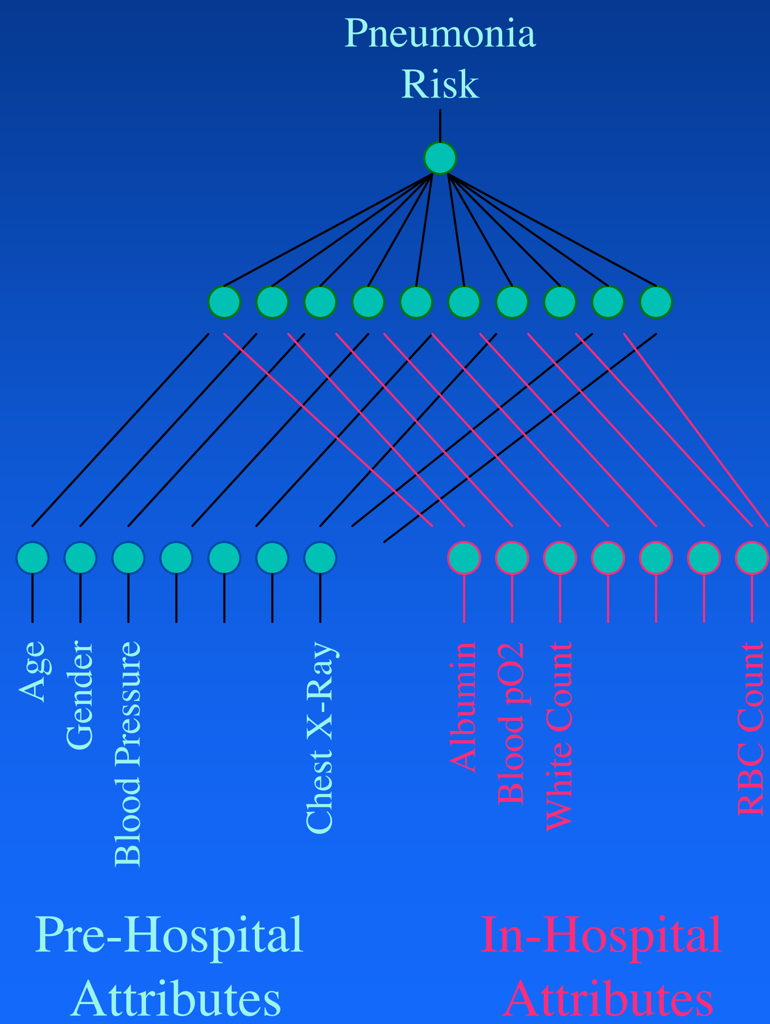
- color camera on Xavier robot
- main tasks: **doorknob location and door type**
- 8 extra tasks (training signals collected by mouse):
  - doorway width
  - location of doorway center
  - location of left jamb, right jamb
  - location of left and right edges of door

1D-Doors: Results

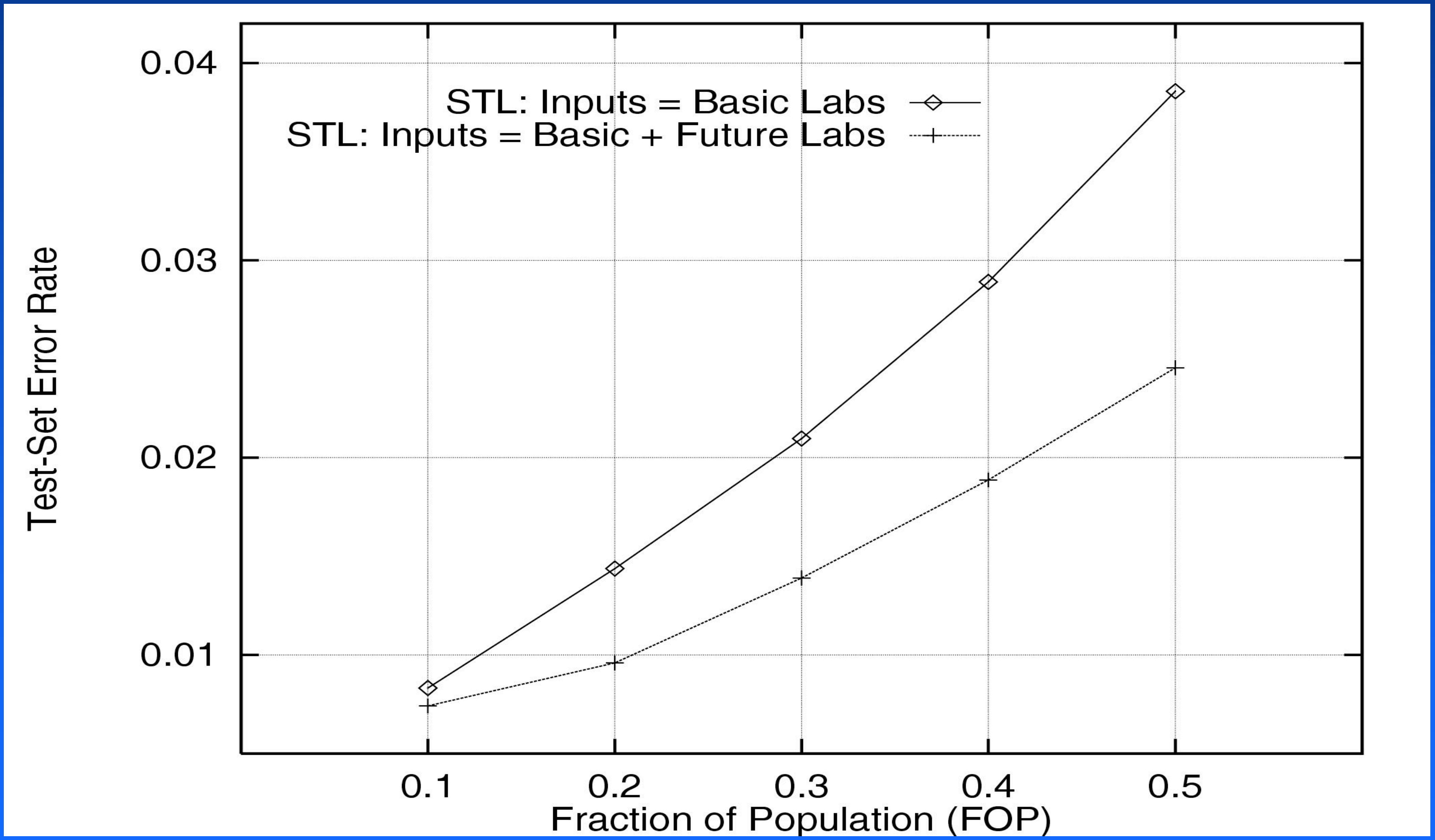
20% more accurate doorknob location

35% more accurate doorway width

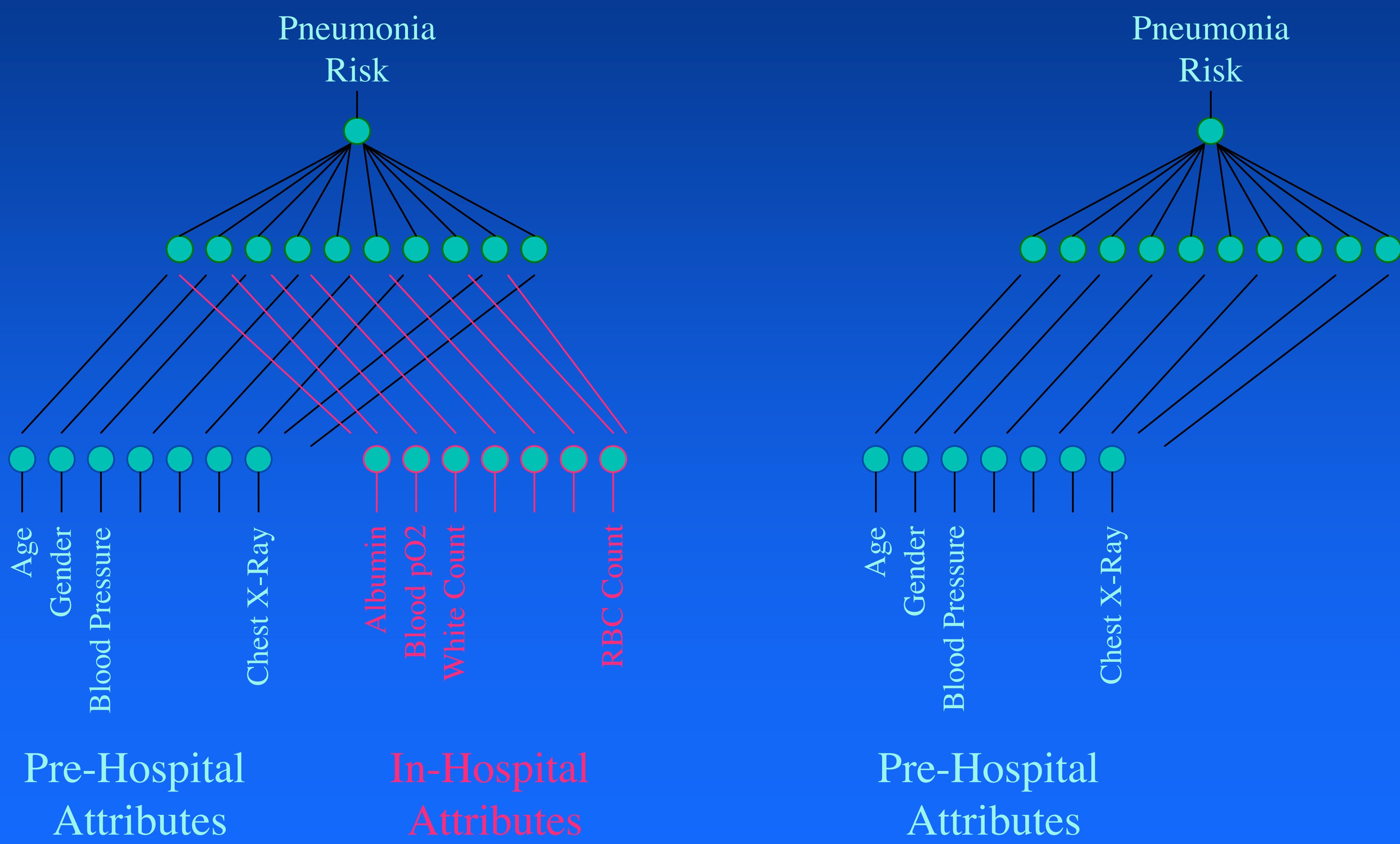
Predicting Pneumonia Risk



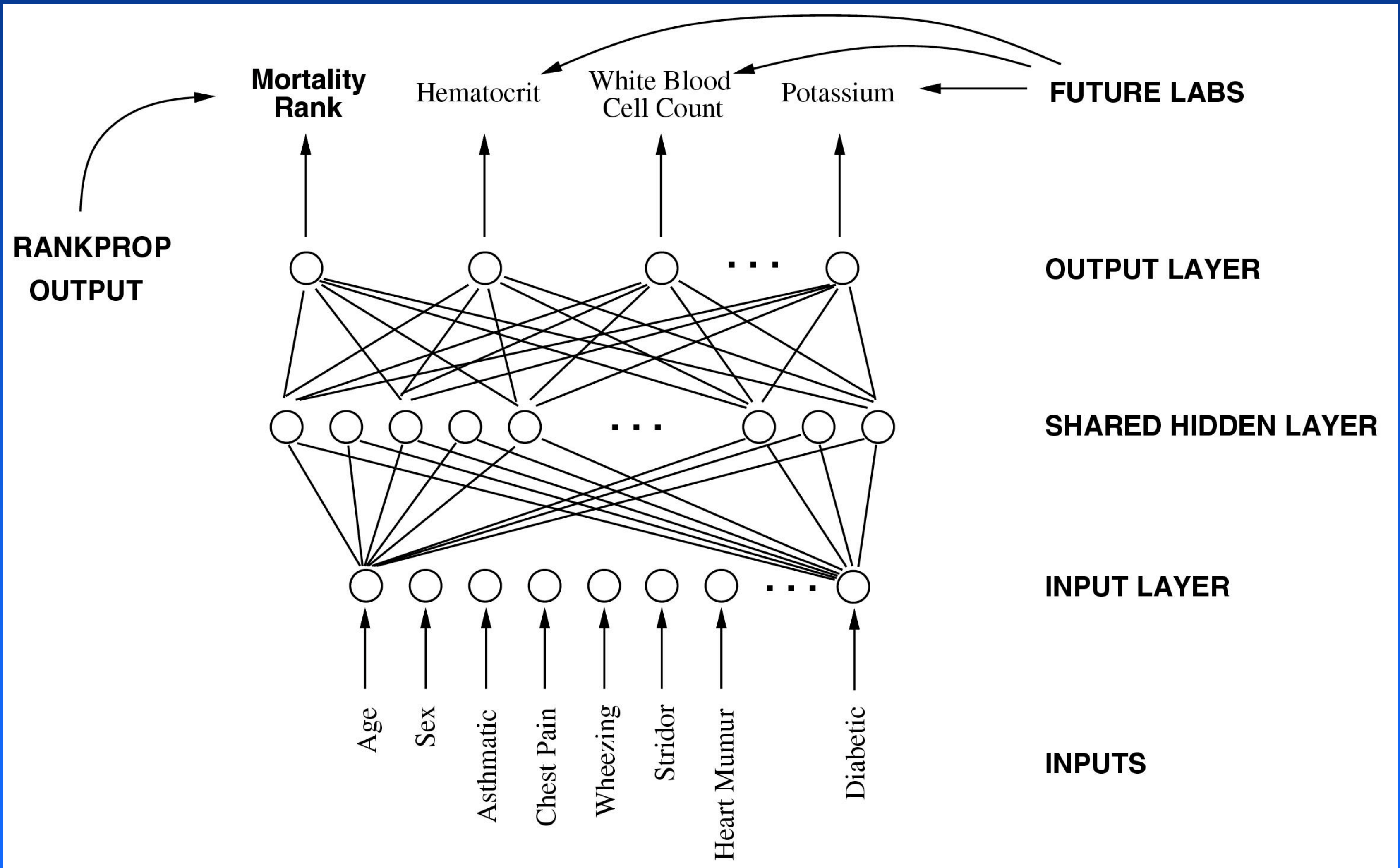
Pneumonia: Hospital Labs as Inputs



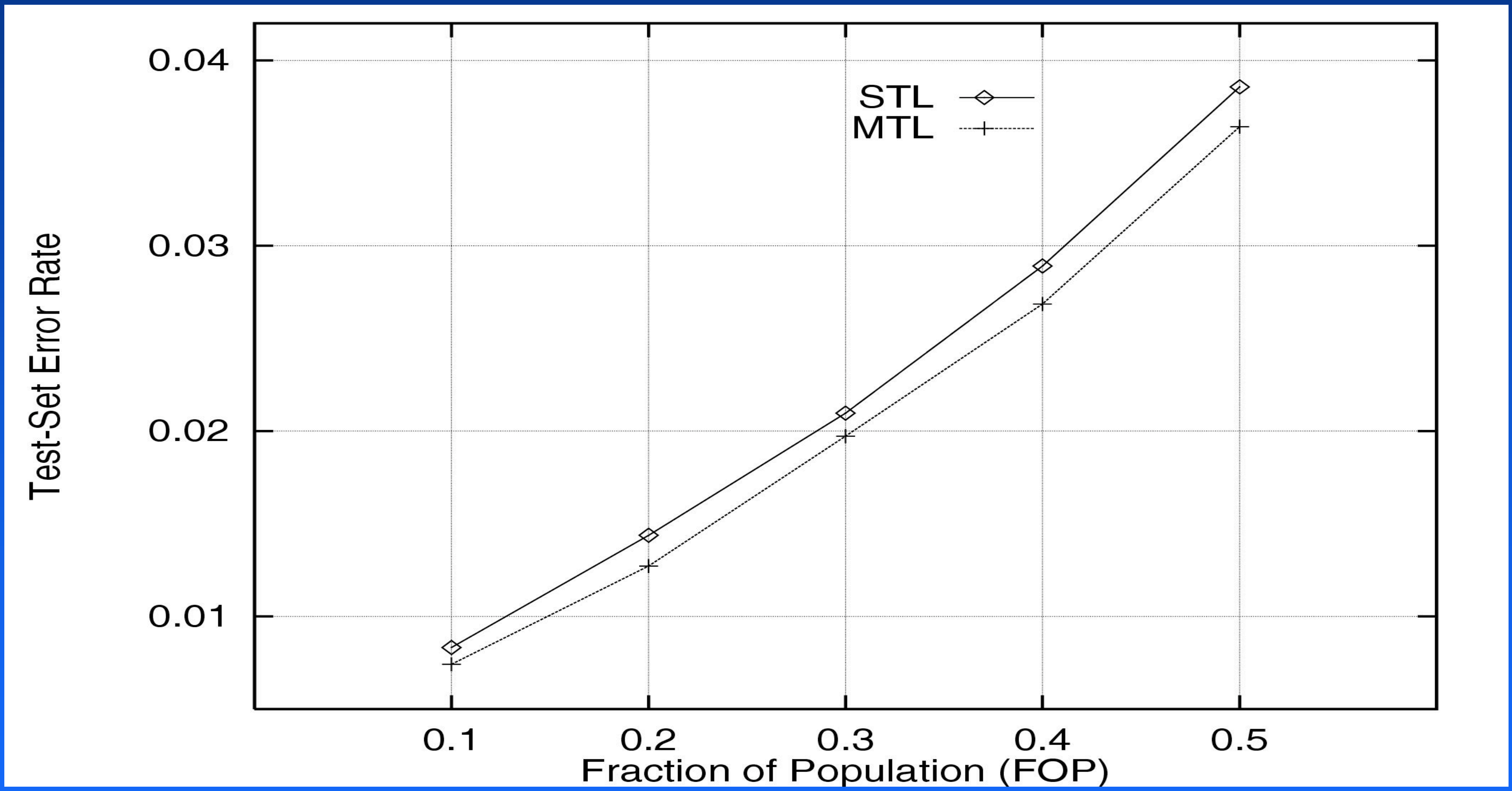
Predicting Pneumonia Risk



Pneumonia #1: Medis



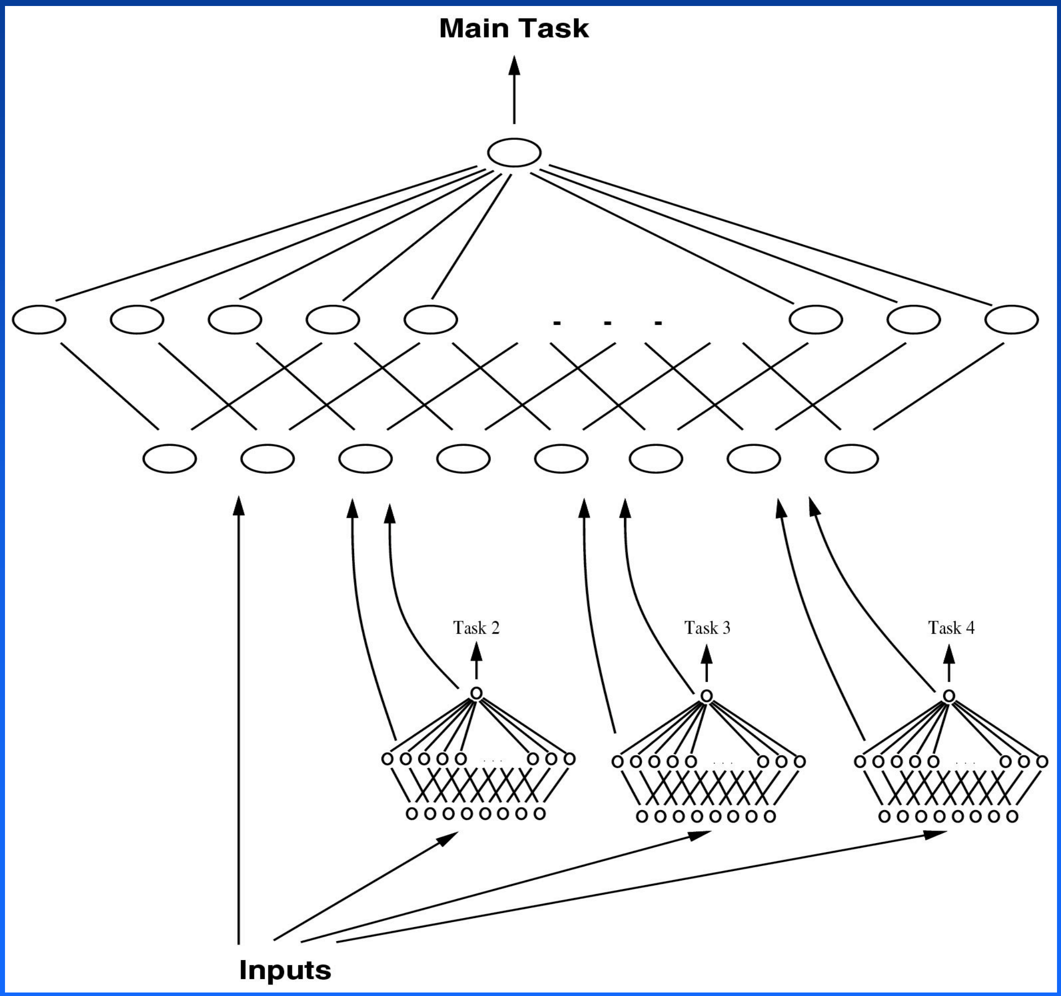
Pneumonia #1: Results



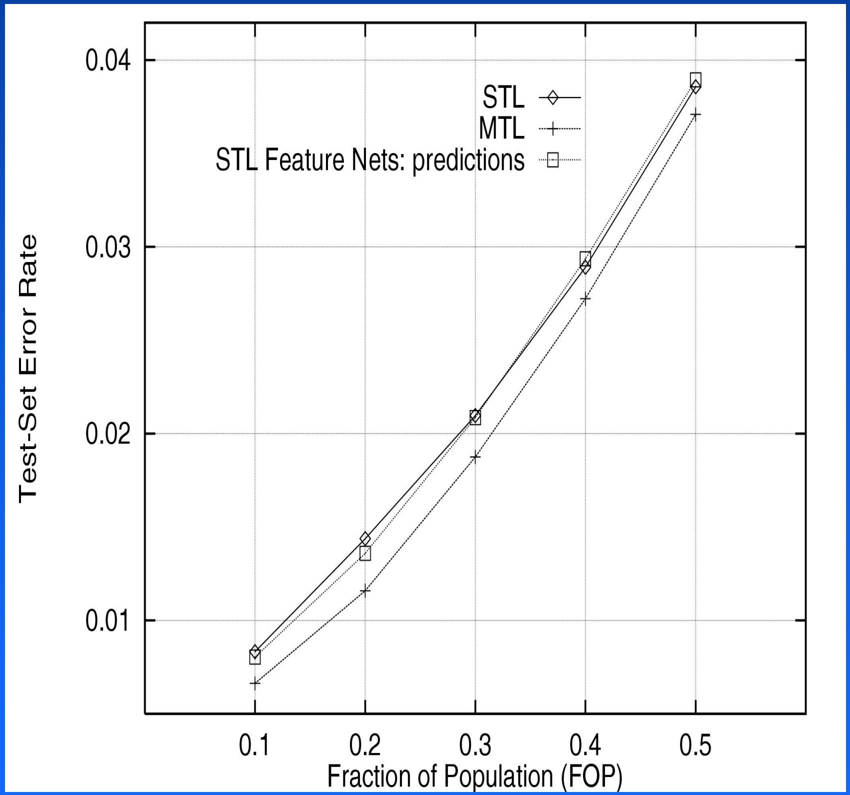
-10.8% -11.8% -6.2% -6.9% -5.7%

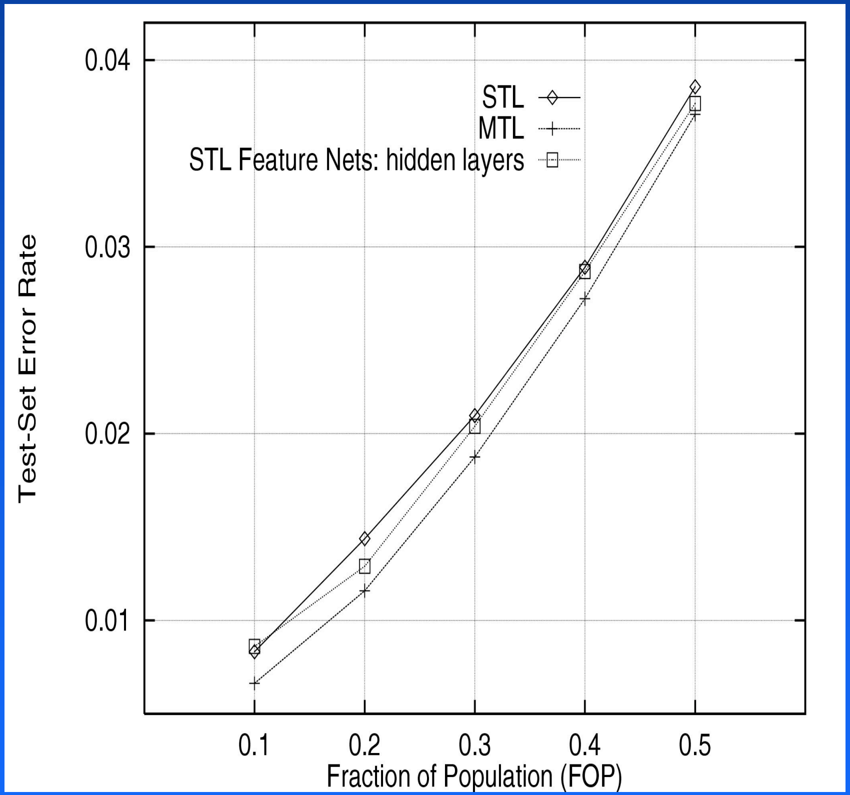
Use imputed values for missing lab tests as extra *inputs*?

Pneumonia #1: Feature Nets



Feature Nets vs. MTL

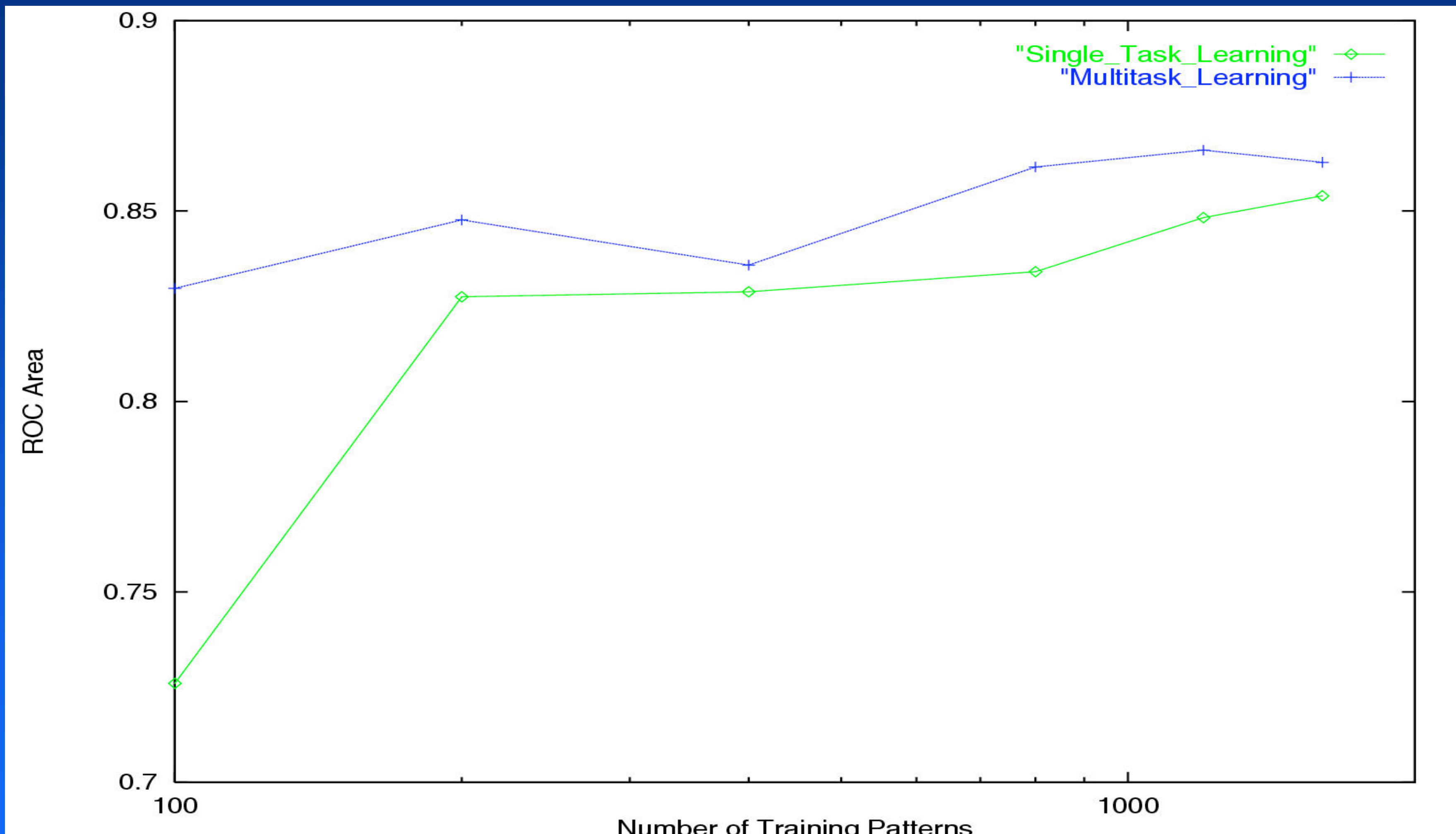




Pneumonia #2: PORT

- 10X fewer cases (2286 patients)
- 10X more input features (200 feats)
- missing features (5% overall, up to 50%)
- main task: dire outcome
- 30 extra tasks currently available
  - dire outcome disjuncts (death, ICU, cardio, ...)
  - length of stay in hospital
  - cost of hospitalization
  - etiology (gramnegative, grampositive, ...)
  - . . .

Pneumonia #2: Results



MTL reduces error >10%

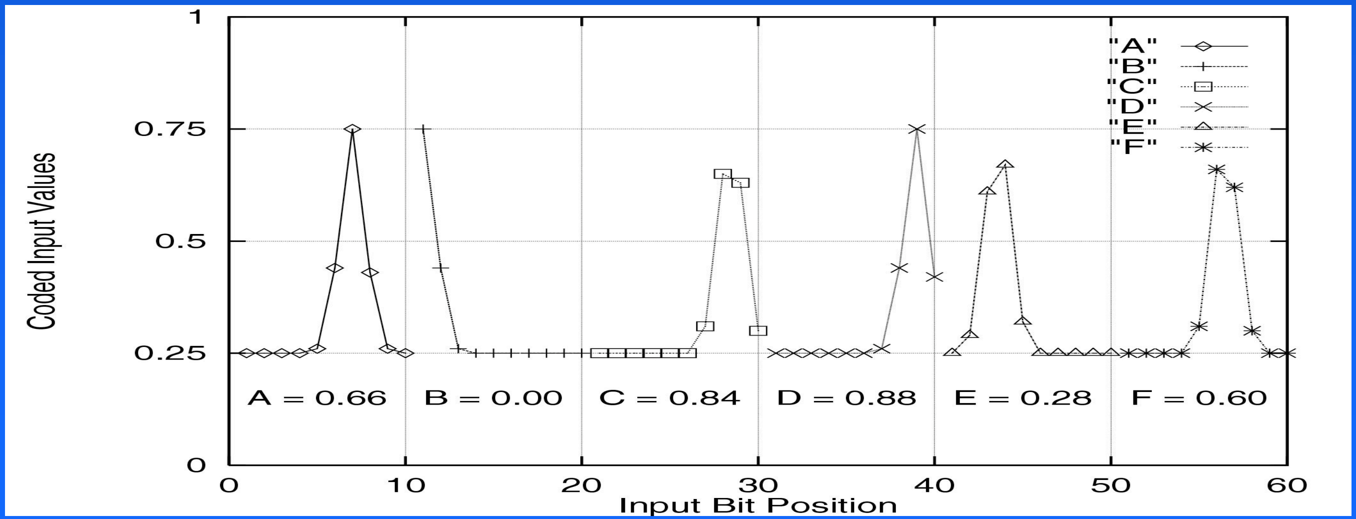
Related?

- related $\not\Rightarrow$ helps learning (e.g., copy task)
- helps learning $\not\Rightarrow$ related (e.g., noise task)
- related $\not\Rightarrow$ correlated (e.g., A+B, A-B)

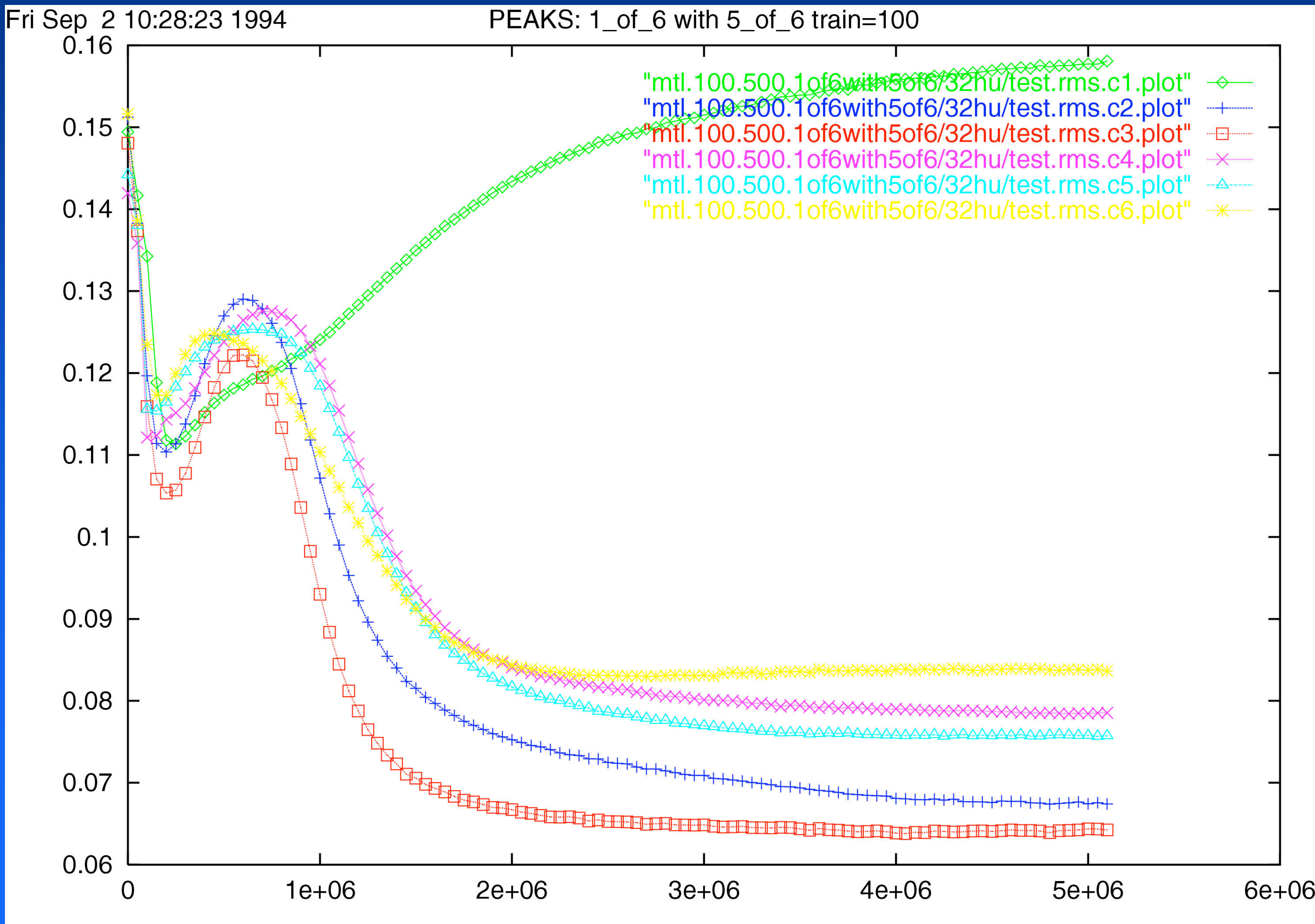
Two tasks are MTL/BP related if there is correlation (positive or negative) between the training signals of one and the hidden layer representation learned for the other

120 Synthetic Tasks

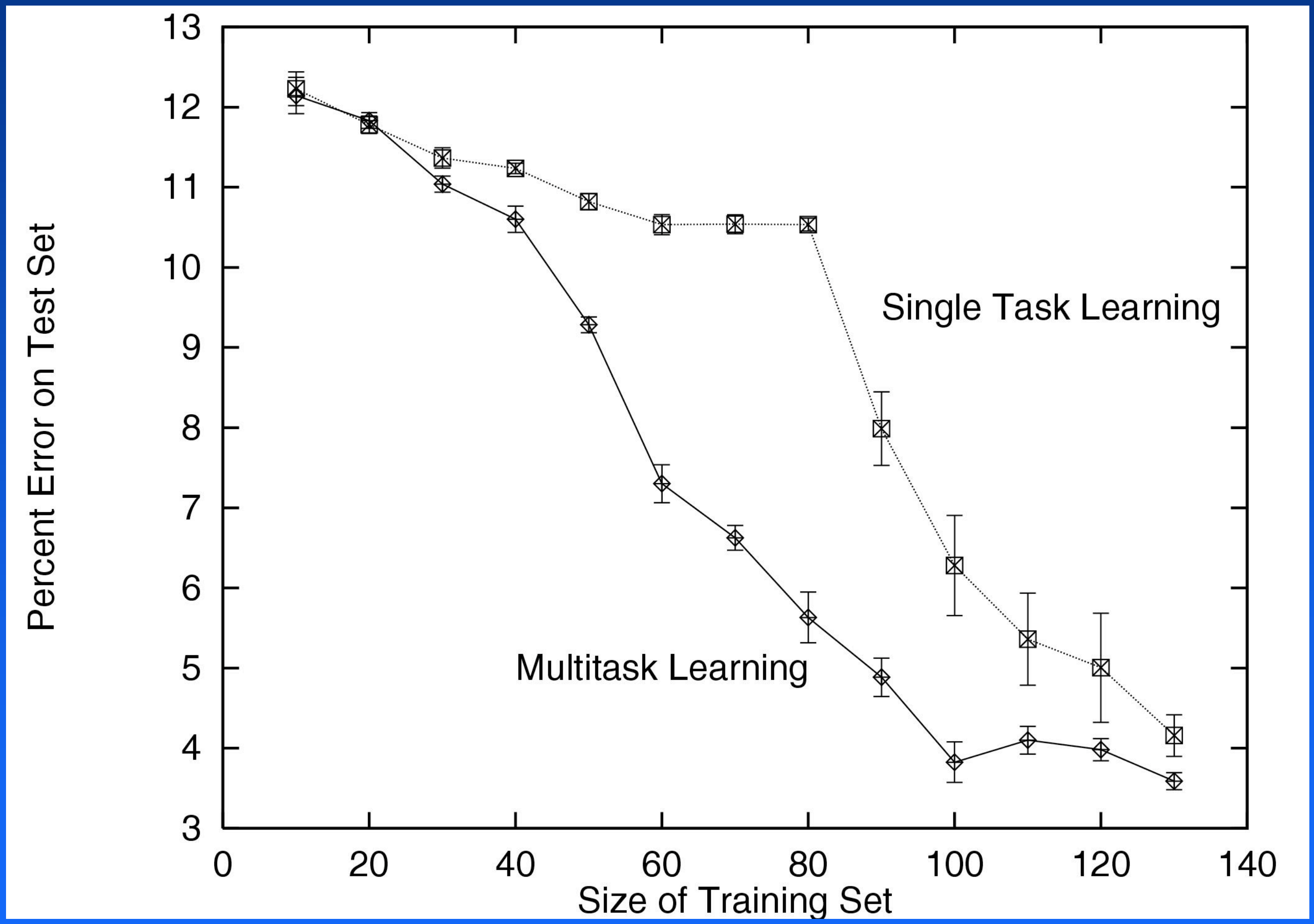
- backprop net not told how tasks are related, but ...
- 120 **Peaks Functions**: A,B,C,D,E,F (0.0,1.0)
  - P 001 = If (A > 0.5) Then B, Else C
  - P 002 = If (A > 0.5) Then B, Else D
  - P 014 = If (A > 0.5) Then E, Else C
  - P 024 = If (B > 0.5) Then A, Else F
  - P 120 = If (F > 0.5) Then E, Else D



Peaks Functions: Results



Peaks Functions: Results

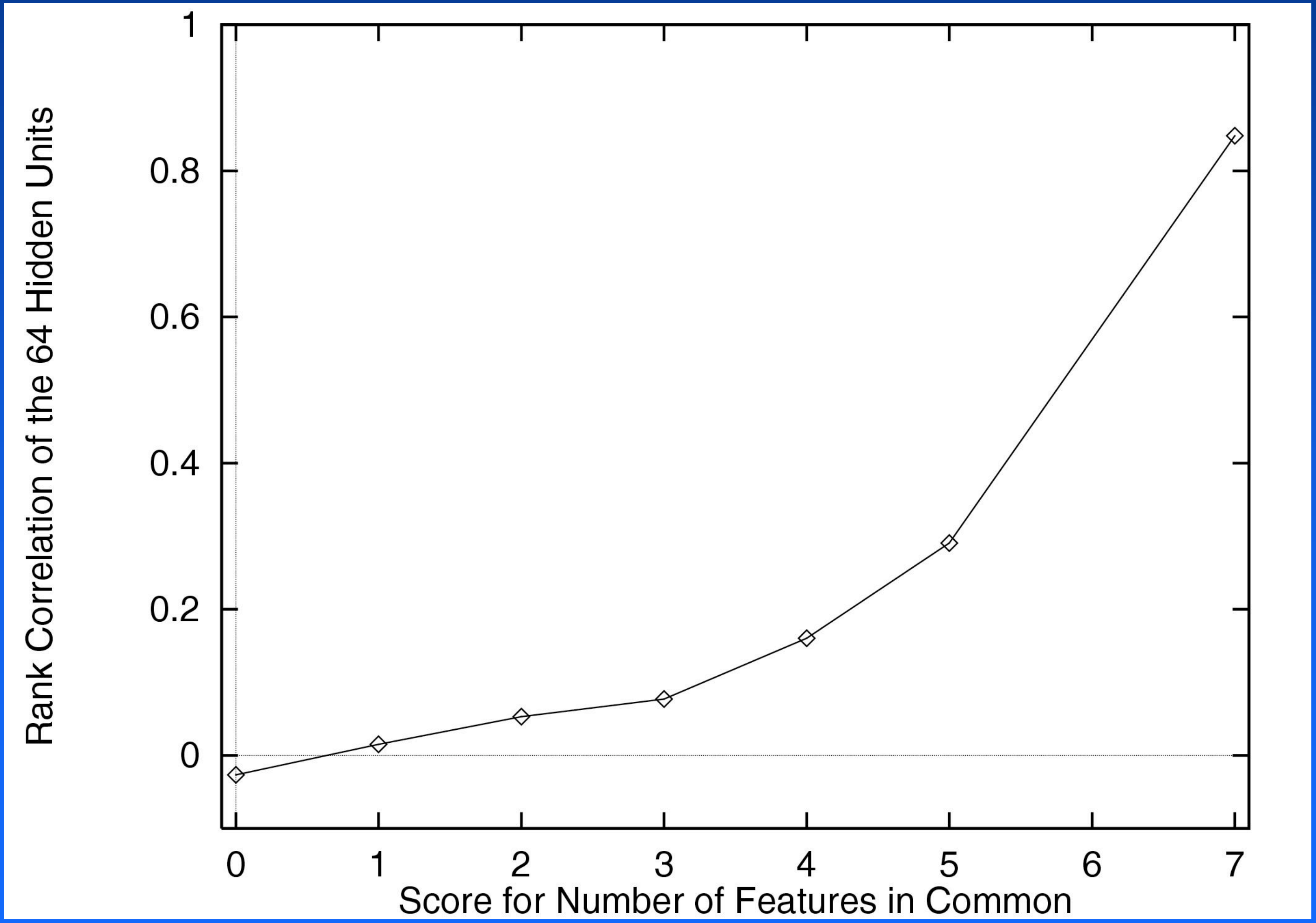


courtesy Joseph O'Sullivan

MTL nets cluster tasks

by *function*

Peaks Functions: Clustering



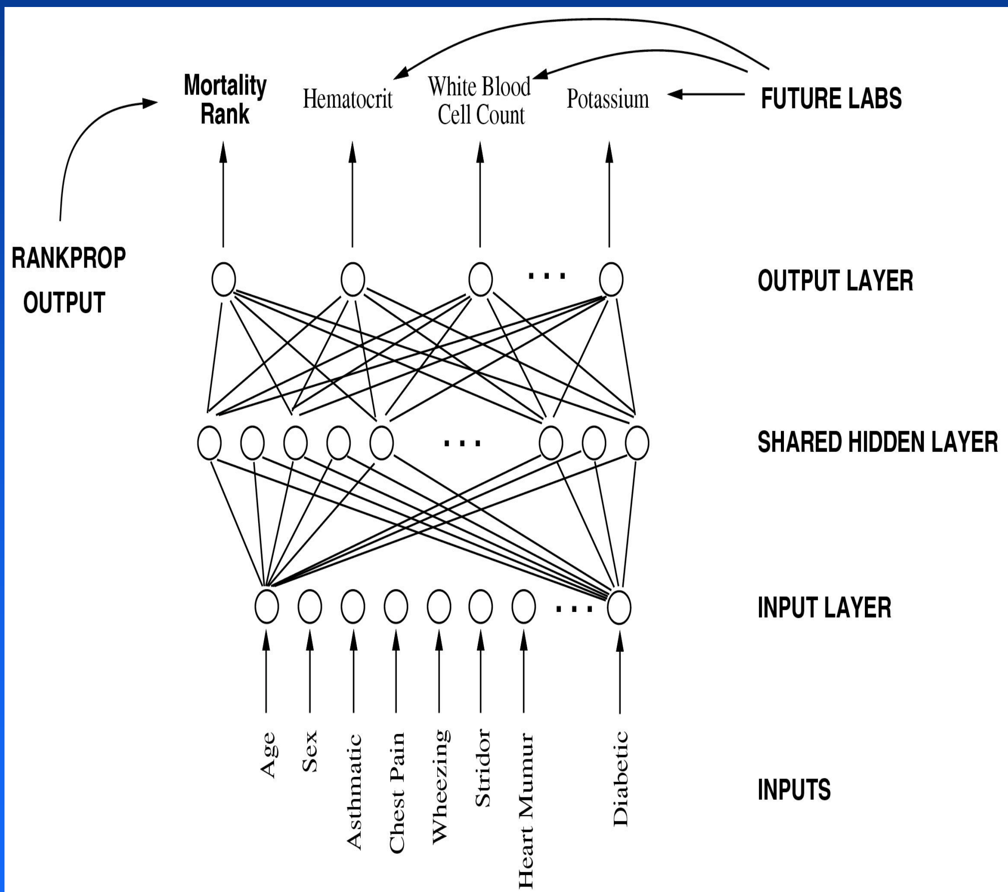
Heuristics: When to use MTL?

- using future to predict present
- time series
- disjunctive/conjunctive tasks
- multiple error metric
- quantized or stochastic tasks
- focus of attention
- sequential transfer
- different data distributions
- hierarchical tasks
- some input features work better as outputs

Multiple Tasks Occur Naturally

- Mitchell’s Calendar Apprentice (CAP)
  - time-of-day (9:00am, 9:30am, ...)
  - day-of-week (M, T, W, ...)
  - duration (30min, 60min, ...)
  - location (Tom’s office, Dean’s office, 5409, ...)

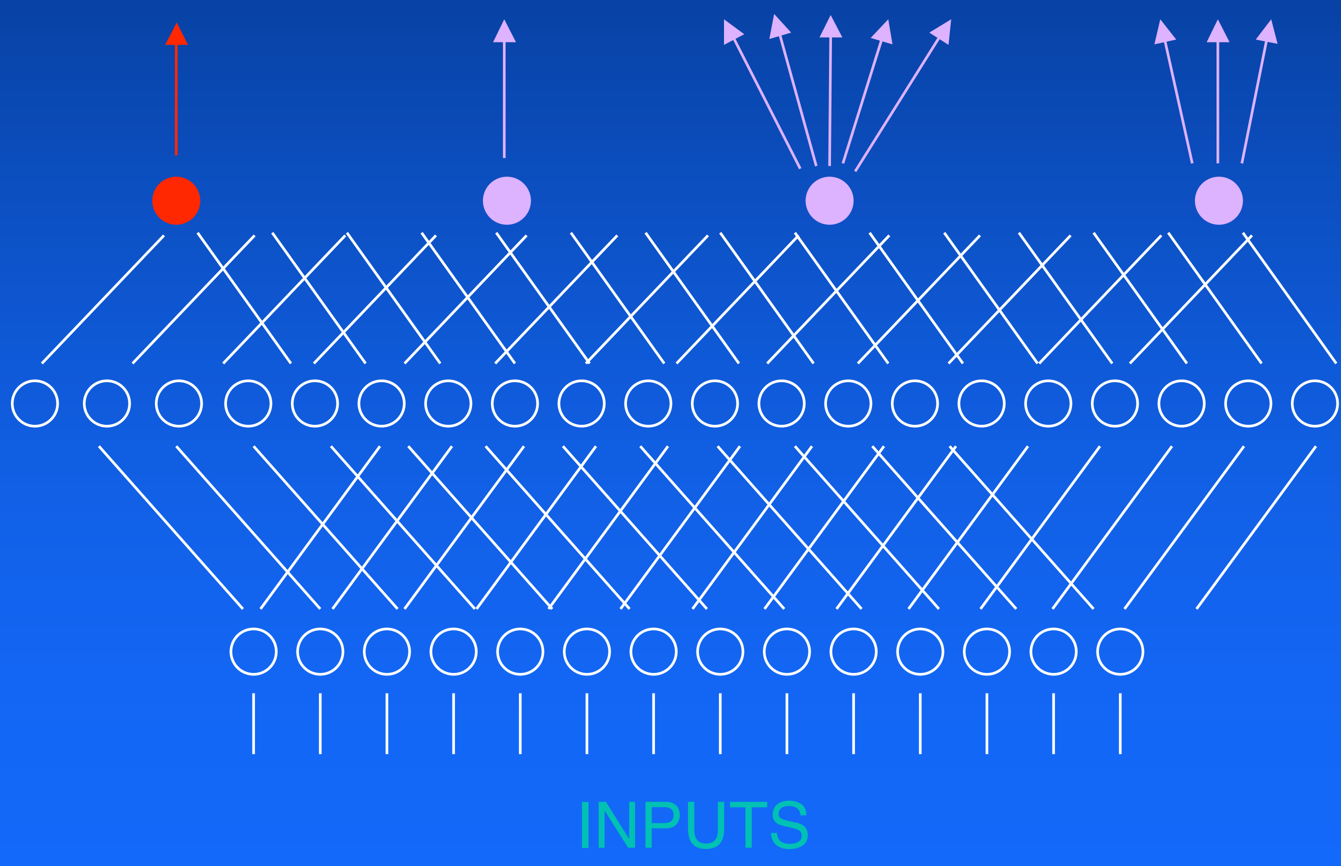
Using Future to Predict Present



- **medical domains**
- autonomous vehicles and robots
- **time series**
  - stock market
  - economic forecasting
  - weather prediction
  - spatial series
- many more

Disjunctive/Conjunctive Tasks

DireOutcome = ICU v Complication v Death

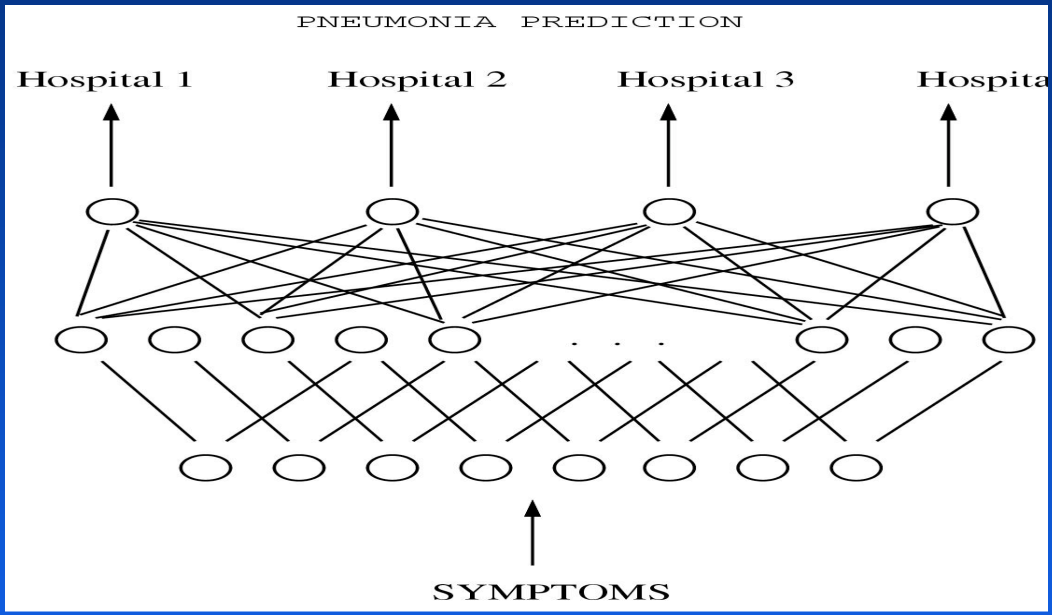


Focus of Attention

- 1D-ALVINN:
  - centerline
  - left and right edges of road

removing centerlines from 1D-ALVINN images hurts MTL accuracy more than STL accuracy

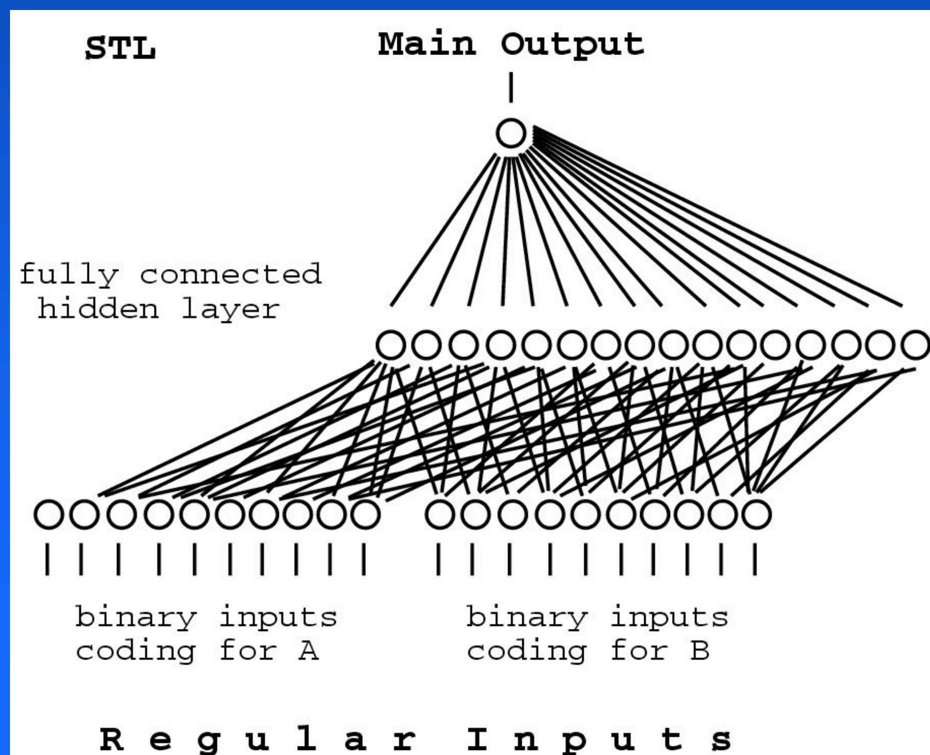
Different Data Distributions



- Hospital 1: 50 cases, rural (Green Acres)
- Hospital 2: 500 cases, urban (Des Moines)
- Hospital 3: 1000 cases, elderly suburbs (Florida)
- Hospital 4: 5000 cases, young urban (LA,SF)

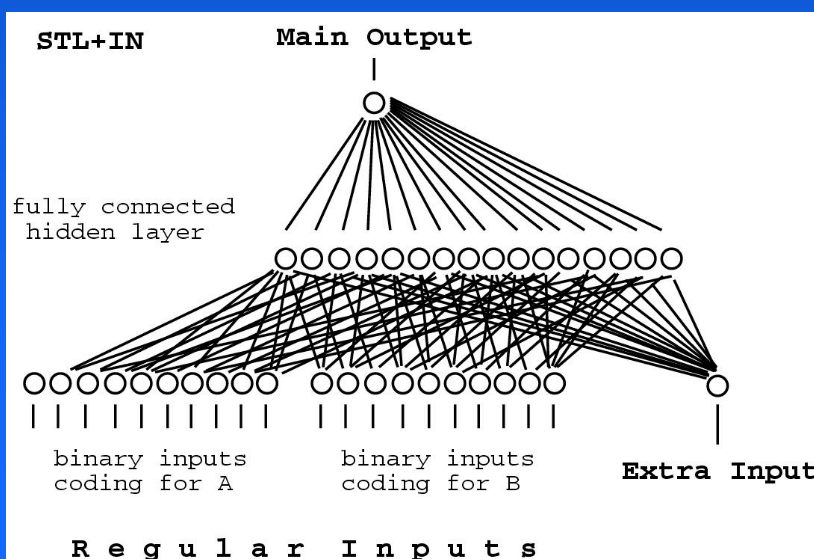
Some Inputs are Better as Outputs

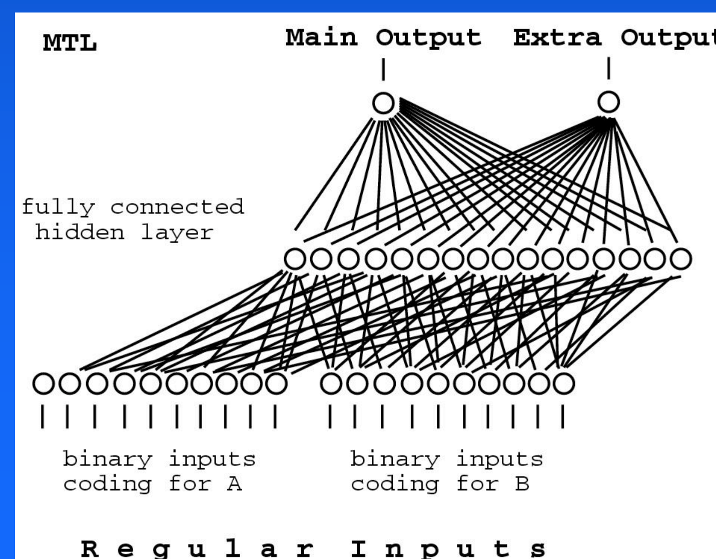
- MainTask = Sigmoid(A)+Sigmoid(B)
- A, B $\in$ ($-$5.0, +5.0)
- Inputs A and B coded via 10-bit binary code



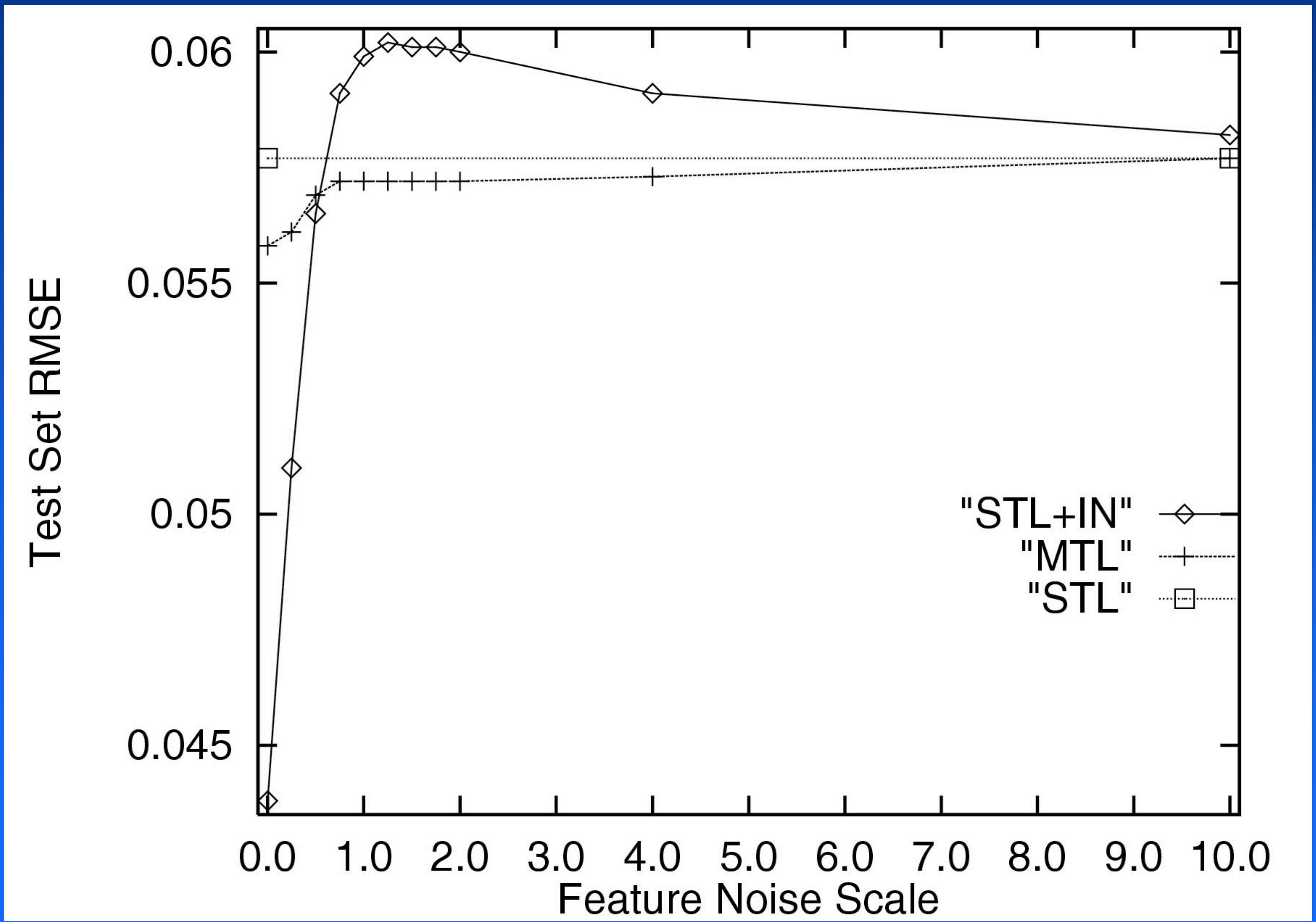
Some Inputs are Better as Outputs

- MainTask = Sigmoid(A)+Sigmoid(B)
- Extra Features:
  - EF1 = Sigmoid(A) + □ * Noise
  - EF2 = Sigmoid(B) + □ * Noise
  - where □ □ (0.0, 10.0), Noise □ (-1.0, 1.0)

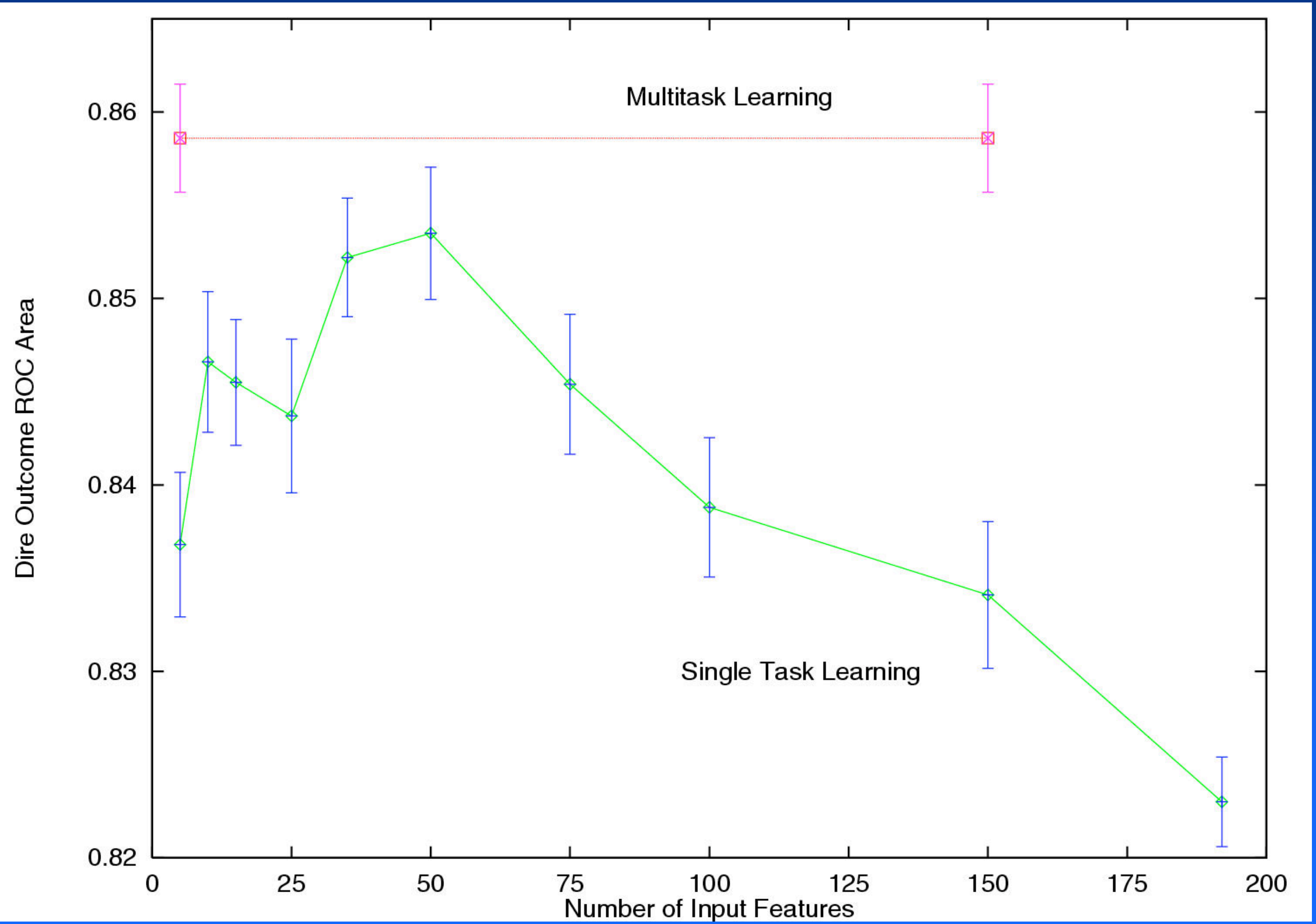




Inputs Better as Outputs: Results



Some Inputs Better as Outputs

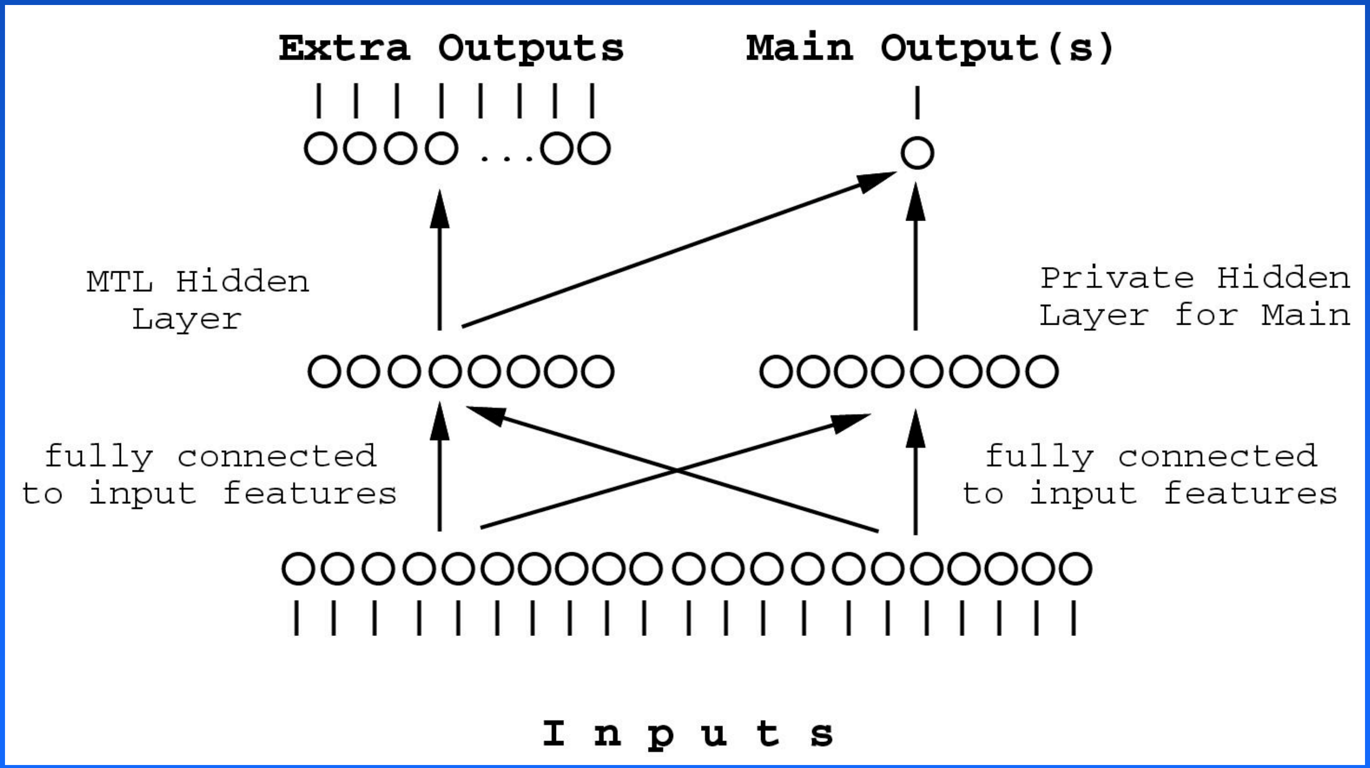


Making MTL/Backprop Better

- Better training algorithm:
  - learning rate optimization
- Better architectures:
  - private hidden layers (overfitting in hidden unit space)
  - using features as both inputs and outputs
  - combining MTL with Feature Nets

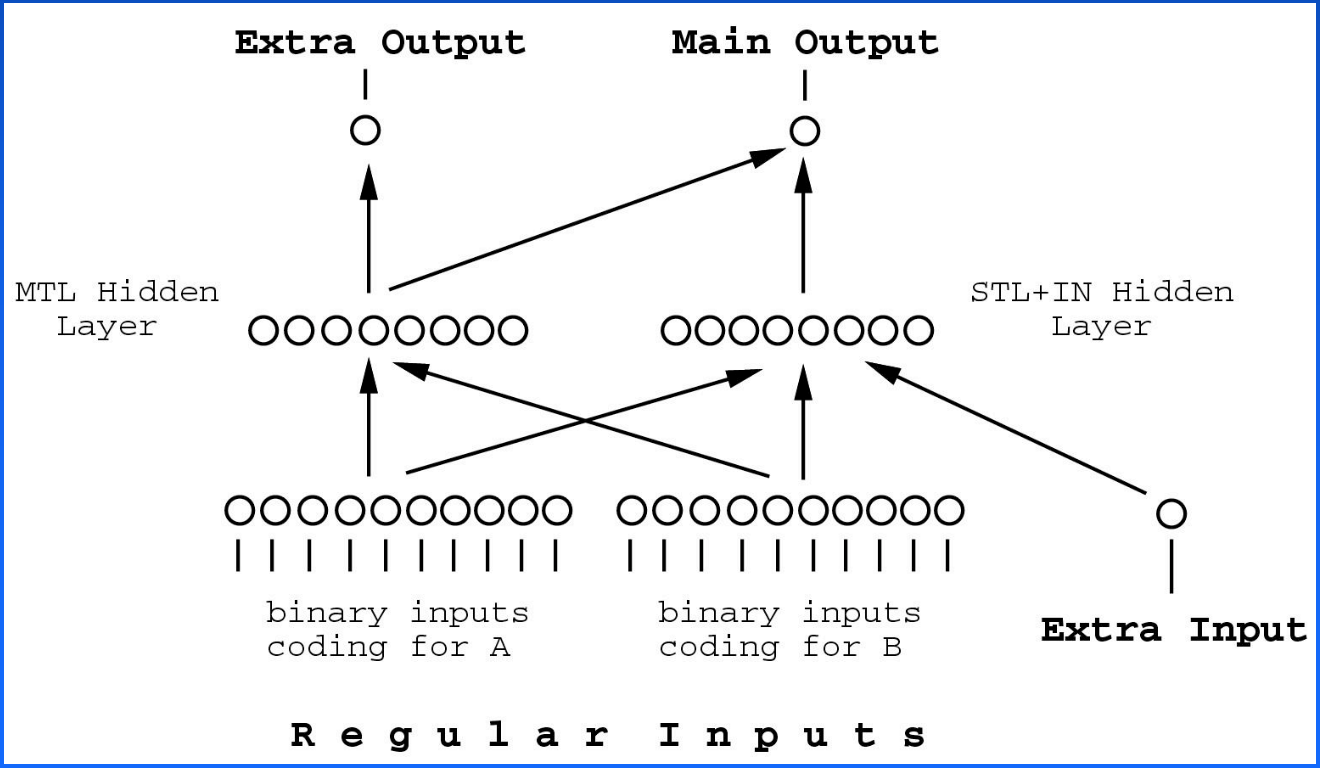
Private Hidden Layers

- many tasks: need many hidden units
- many hidden units: "hidden unit selection problem"
- allow sharing, but without too many hidden units?



Features as Both Inputs & Outputs

- some features help when used as inputs
- some of those also help when used as outputs
- get both benefits in one net?

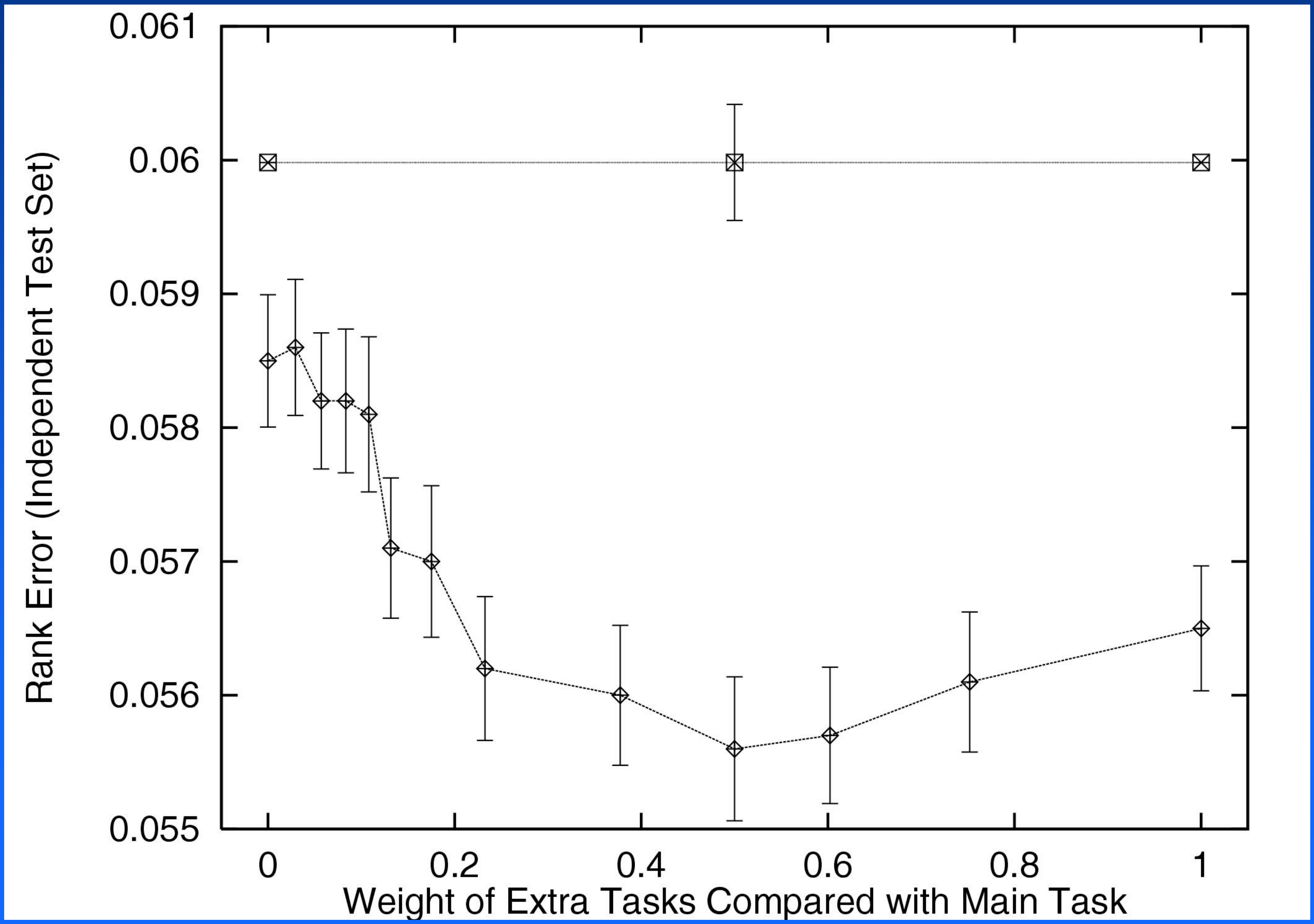


MTL in K-Nearest Neighbor

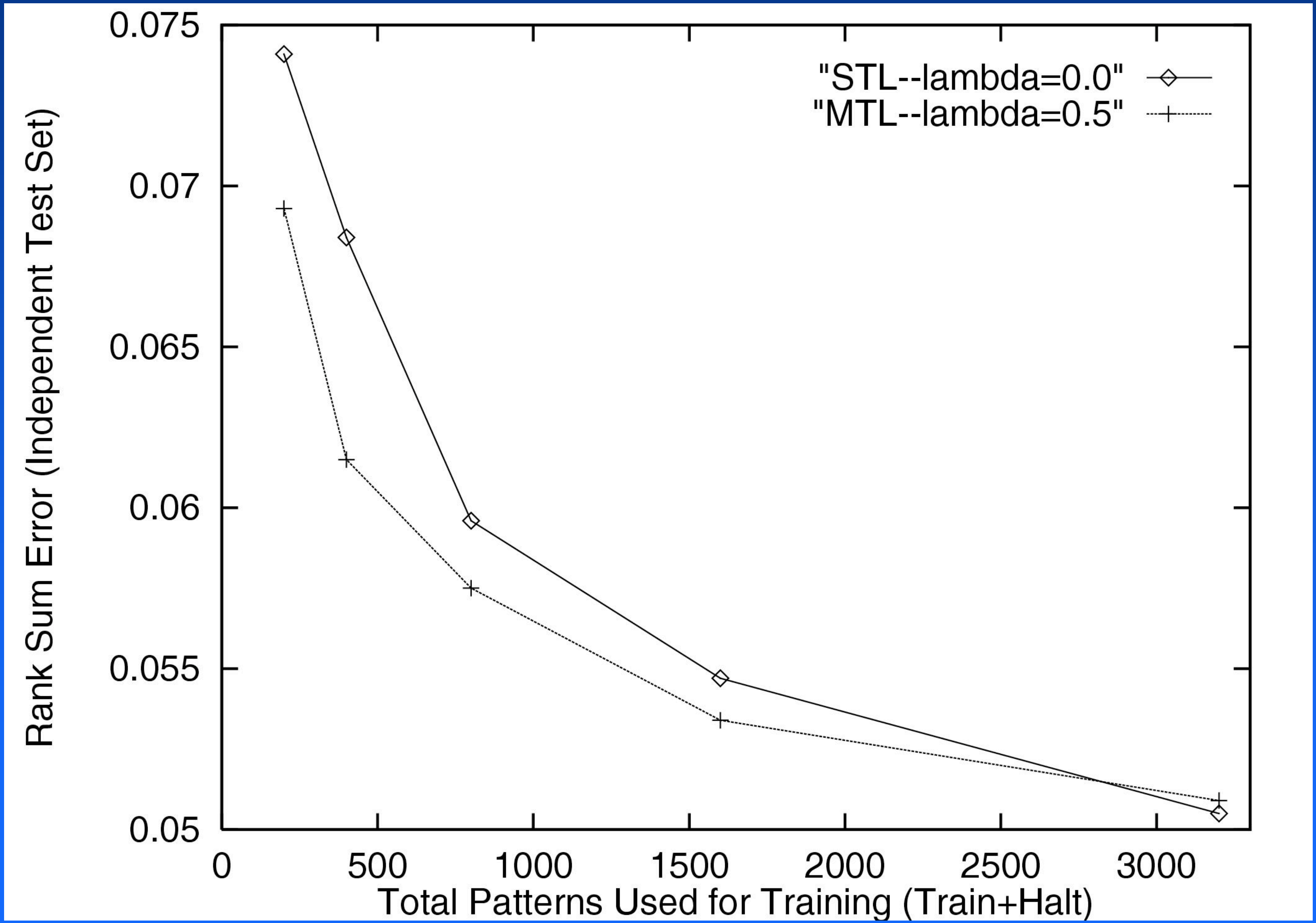
- Most learning methods can MTL:
  - shared representation
  - combine performance of extra tasks
  - control the effect of extra tasks

- MTL in K-Nearest Neighbor:
  - shared rep: distance metric
  - MTLPerf = (1-□)□MainPerf + □ (□□ExtraPerf)

MTL/KNN for Pneumonia #1



MTL/KNN for Pneumonia #1



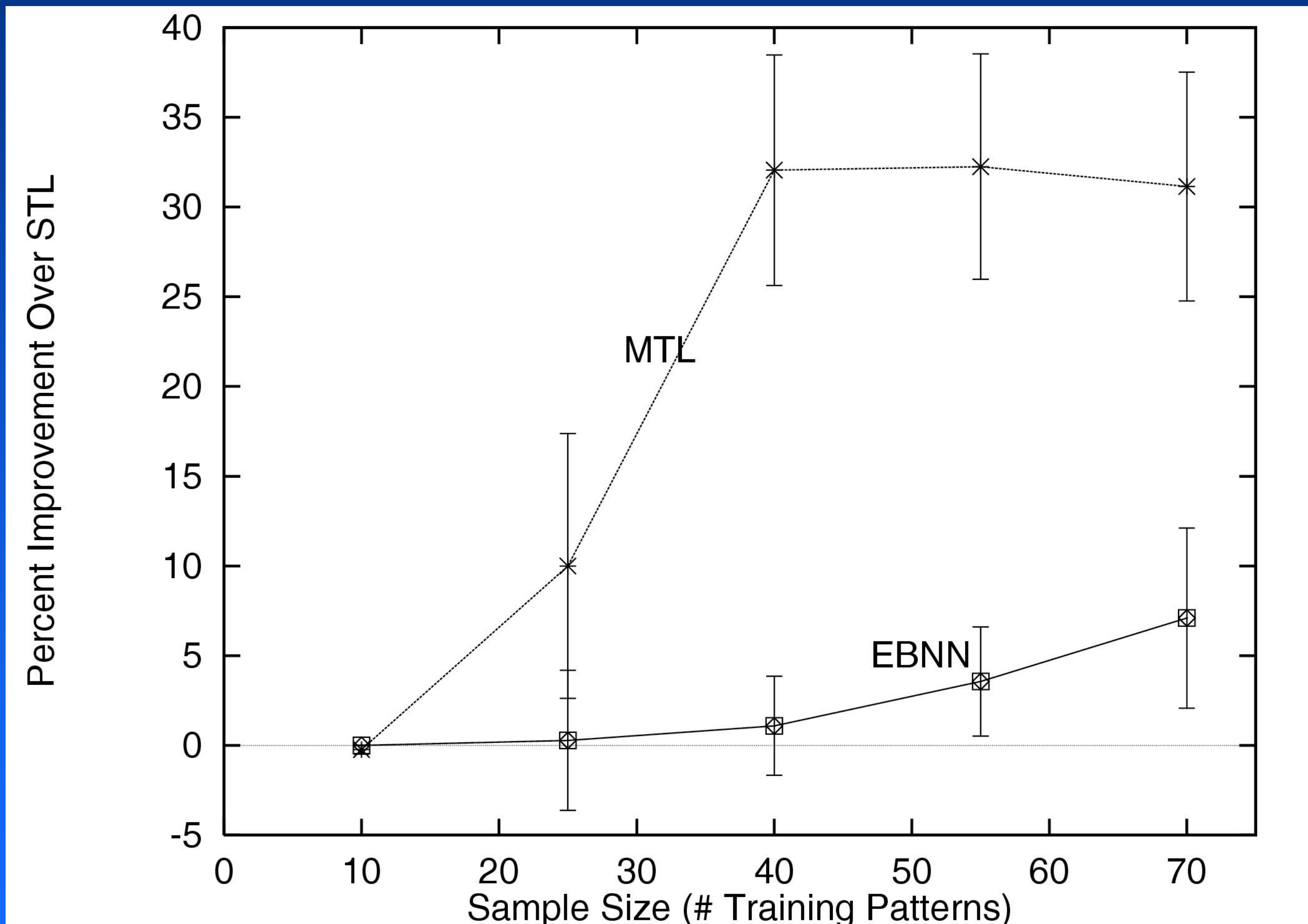
Psychological Plausibility

?

Related Work

– Sejnowski, Rosenberg [1986]: NETtalk
– Pratt, Mostow [1991-94]: serial transfer in bp nets
– Suddarth, Kergiosen [1990]: 1st MTL in bp nets
– Abu-Mostafa [1990-95]: catalytic hints
– Abu-Mostafa, Baxter [92,95]: transfer PAC models
– Dietterich, Hild, Bakiri [90,95]: bp vs. ID3
– Pomerleau, Baluja: other uses of hidden layers
– Munro [1996]: extra tasks to decorrelate experts
– Breiman [1995]: Curds & Whey
– de Sa [1995]: minimizing disagreement
– Thrun, Mitchell [1994,96]: EBNN
– O'Sullivan, Mitchell [now]: EBNN+MTL+Robot

MTL vs. EBNN on Robot Problem



courtesy Joseph O'Sullivan

Parallel vs. Serial Transfer

- all information is in training signals
- information useful to other tasks can be lost training on tasks one at a time
- if we train on extra tasks first, how can we optimize what is learned to help the main task most
- tasks often benefit each other mutually
- parallel training allows related tasks to see the entire trajectory of other task learning

Summary/Contributions

- focus on main task improves performance
- >15 problem types where MTL is applicable:
  - using the future to predict the present
  - multiple metrics
  - focus of attention
  - different data populations
  - using inputs as extra tasks
  - . . . (at least 10 more)

most real-world problems fit one of these

Summary/Contributions

- applied MTL to a dozen problems, some not created for MTL
  - MTL helps most of the time
  - benefits range from 5%-40%
- ways to improve MTL/Backprop
  - learning rate optimization
  - private hidden layers
  - MTL Feature Nets
- MTL nets do unsupervised clustering
- algs for MTL kNN and MTL Decision Trees

Future MTL Work

- output selection
- scale to 1000's of extra tasks
- compare to Bayes Nets
- learning rate optimization

Theoretical Models of Parallel Xfer

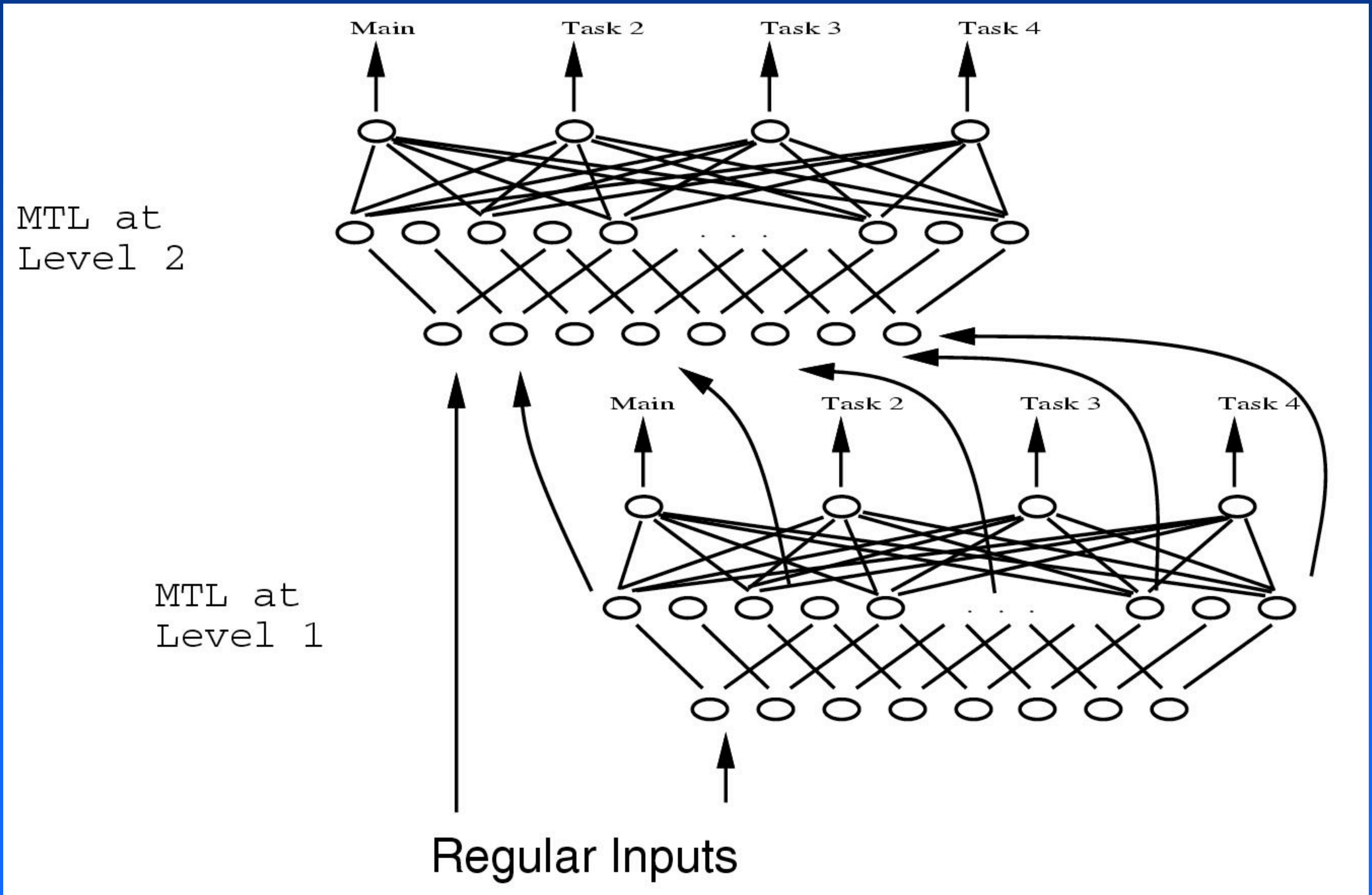
- PAC models based on VC-dim or MDL
  - unreasonable assumptions
    - fixed size hidden layers
    - all tasks generated by one hidden layer
    - backprop is ideal search procedure
  - predictions do not fit observations
    - have to add hidden units
  - main problems:
    - can't take behavior of backprop into account
    - not enough is known about capacity of backprop nets

Learning Rate Optimization

- optimize learning rates of extra tasks
- goal is maximize generalization of main task
- ignore performance of extra tasks
- expensive!

- performance on extra tasks improves 9%!

MTL Feature Nets



Acknowledgements

- advisors: Mitchell & Simon
- committee: Pomerleau & Dietterich
- CEHC: Cooper, Fine, Buchanan, et al.
- co-authors: Baluja, de Sa, Freitag
- robot Xavier: O'Sullivan, Simmons
- discussion: Fahlman, Moore, Touretzky
- funding: NSF, ARPA, DEC, CEHC, JPRC
- SCS/CMU: *a great place to do research*
- spouse: Diane