

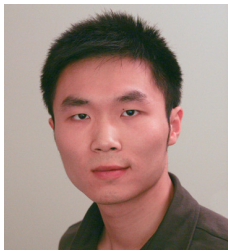


THE UNIVERSITY  
of NORTH CAROLINA  
at CHAPEL HILL

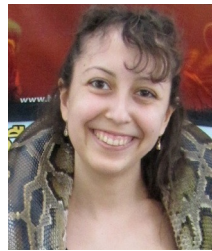


STANFORD  
HCI GROUP

# Scalable Multi-Label Annotation



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Li Fei-Fei



# Multi-label annotation

Data Item	Labels					
	Table	Chair	Horse	Dog	Cat	Bird
	+	+	-	-	-	-

**Task:** Crowdsource object labels for images.

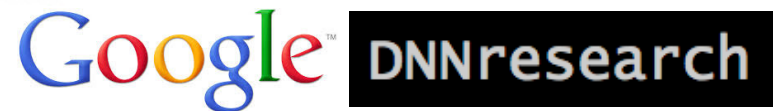
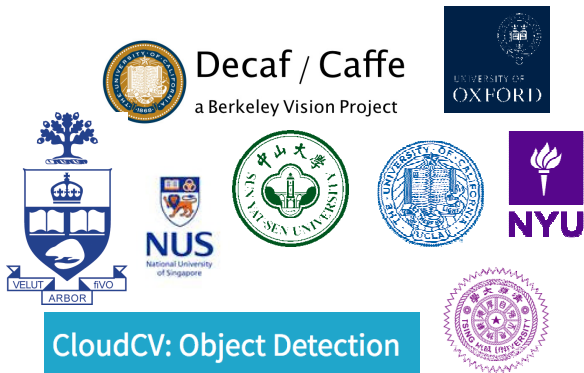
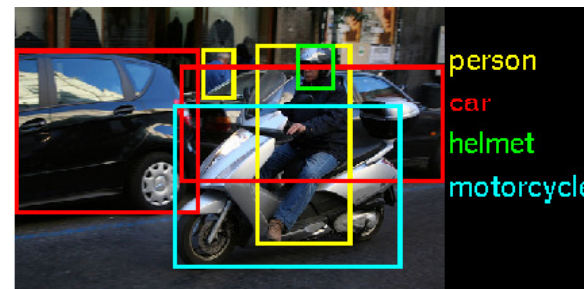
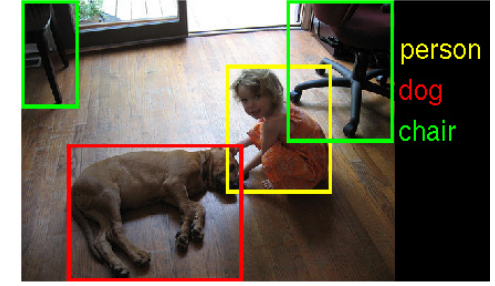
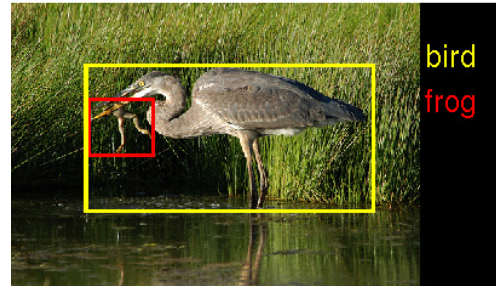
**Application:** Benchmarking, training, modeling

**Generalization:**

- musical attributes of songs
- actions in movies
- sentiments in documents

# Large-Scale Visual Recognition Challenge ILSVRC 2010-2014

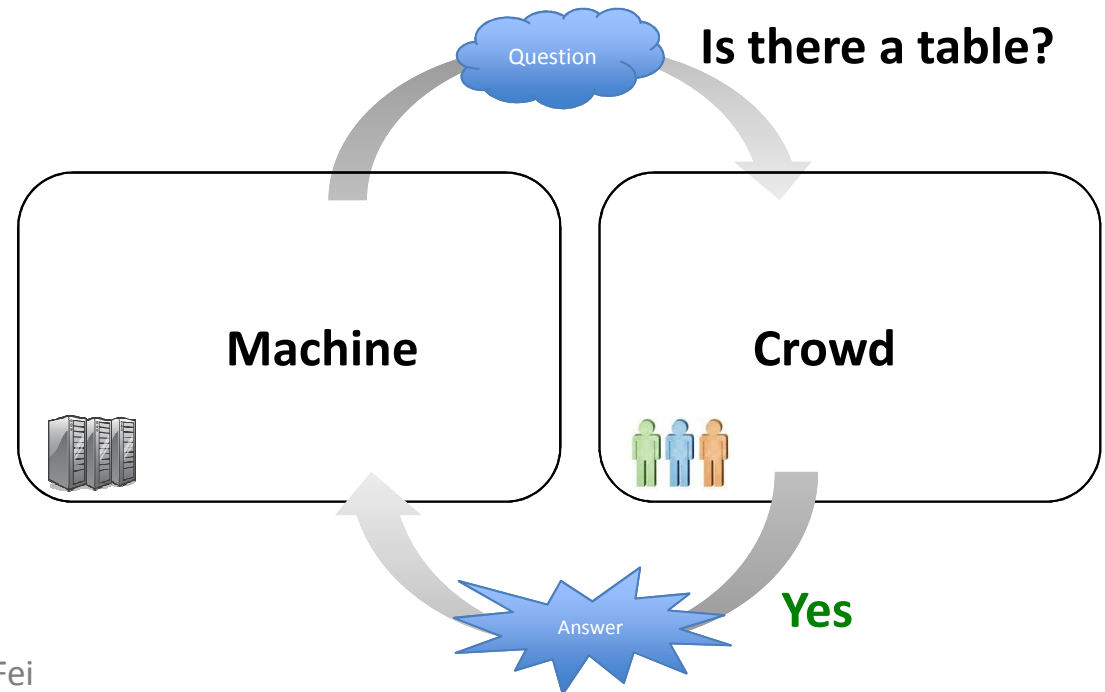
Current focus:  
200 Category Detection  
(~100,000 fully labeled images)



# Naïve approach: ask for each object



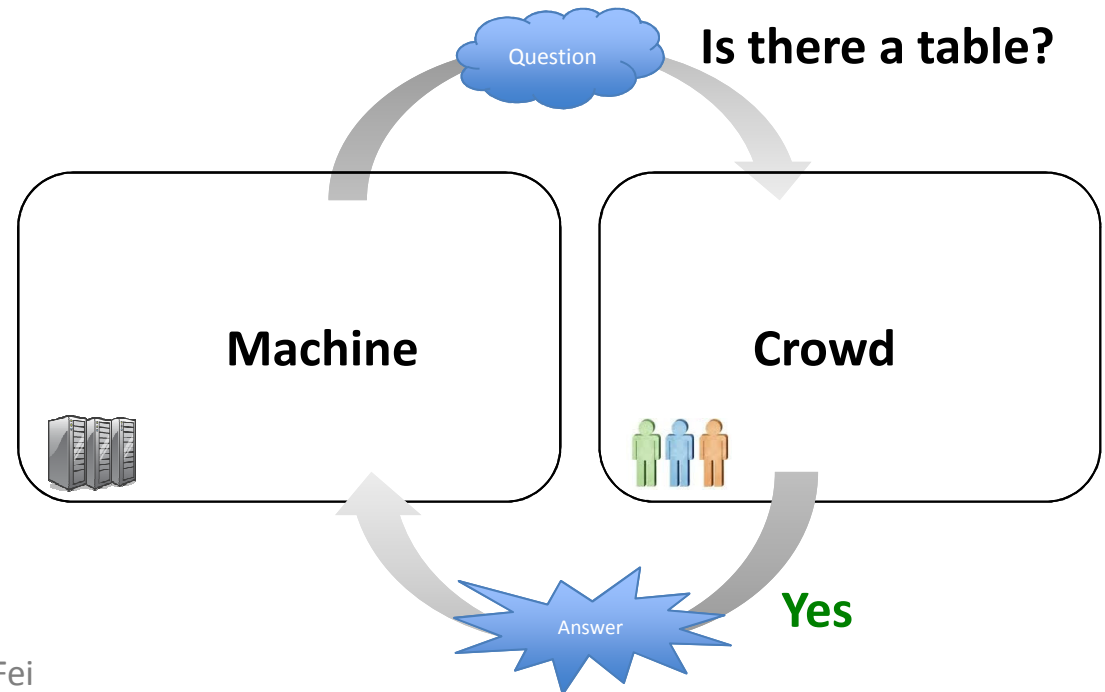
Table	Chair	Horse	Dog	Cat	Bird
?	?	?	?	?	?



# Naïve approach: ask for each object



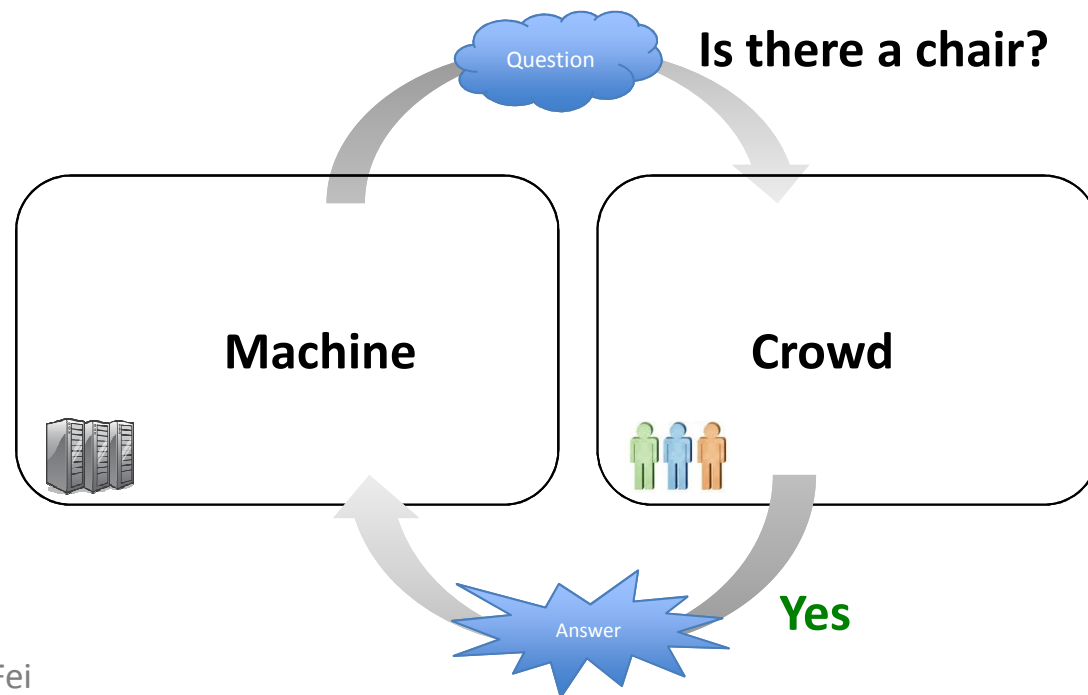
Table	Chair	Horse	Dog	Cat	Bird
+	?	?	?	?	?



# Naïve approach: ask for each object



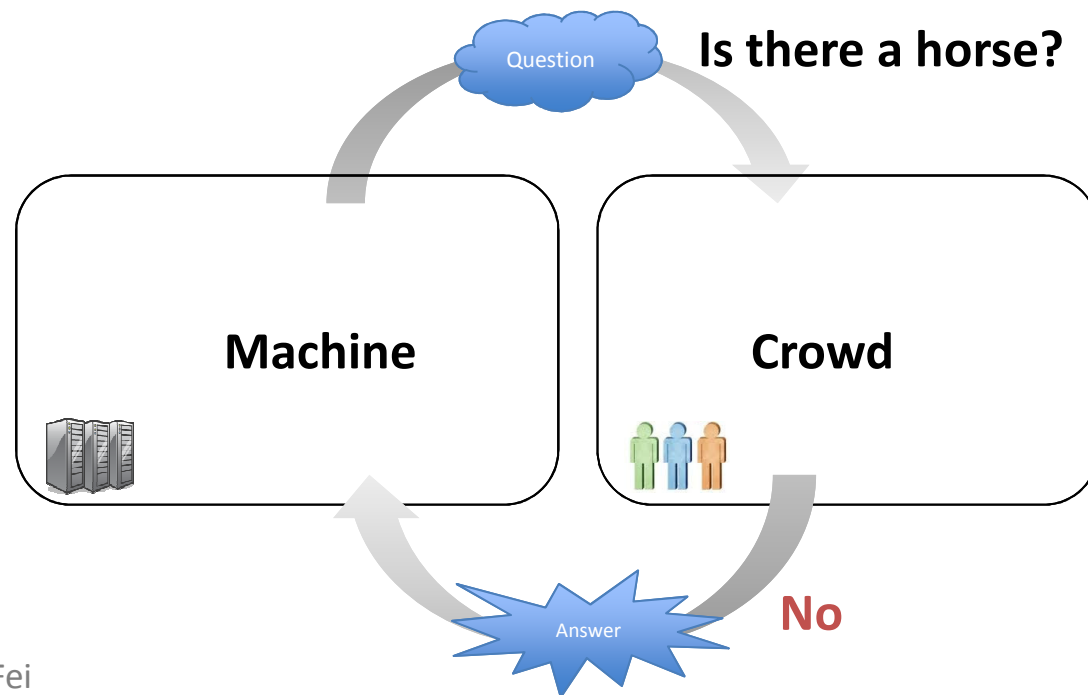
Table	Chair	Horse	Dog	Cat	Bird
+	+	?	?	?	?



# Naïve approach: ask for each object



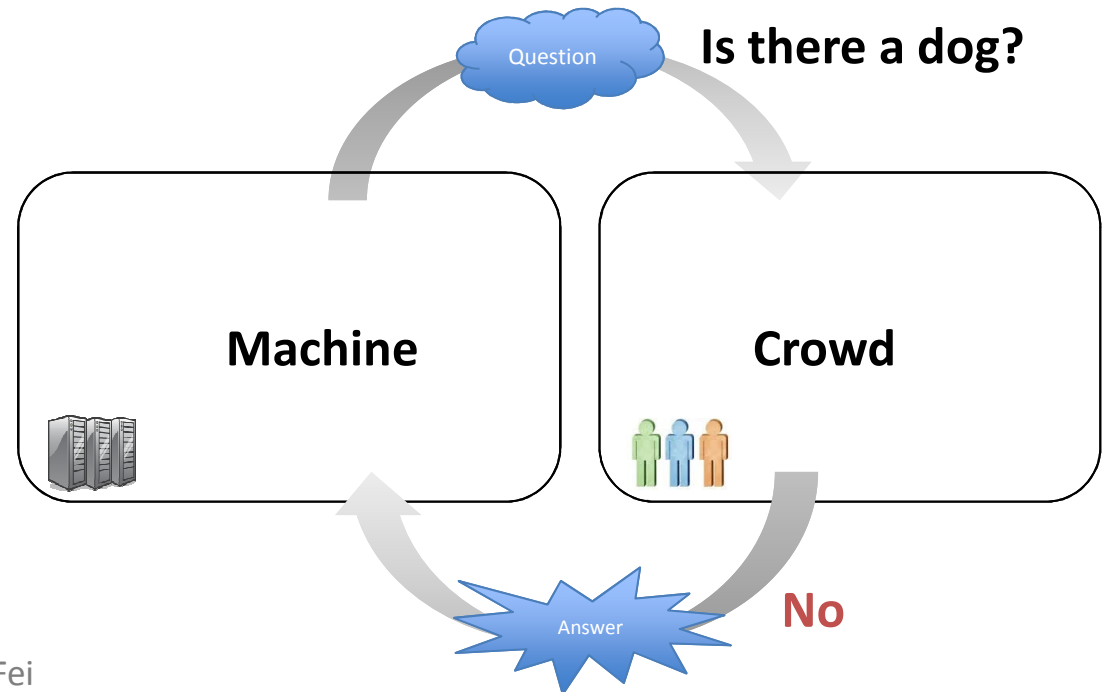
Table	Chair	Horse	Dog	Cat	Bird
+	+	-	?	?	?



# Naïve approach: ask for each object



Table	Chair	Horse	Dog	Cat	Bird
+	+	-	-	?	?

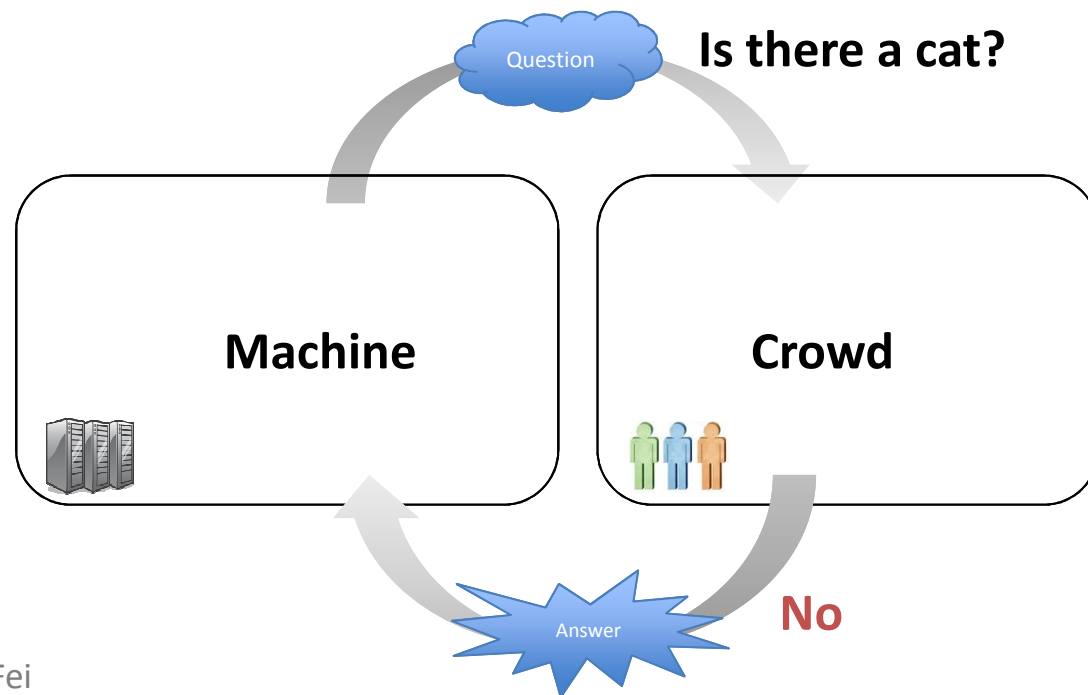




# Naïve approach: ask for each object



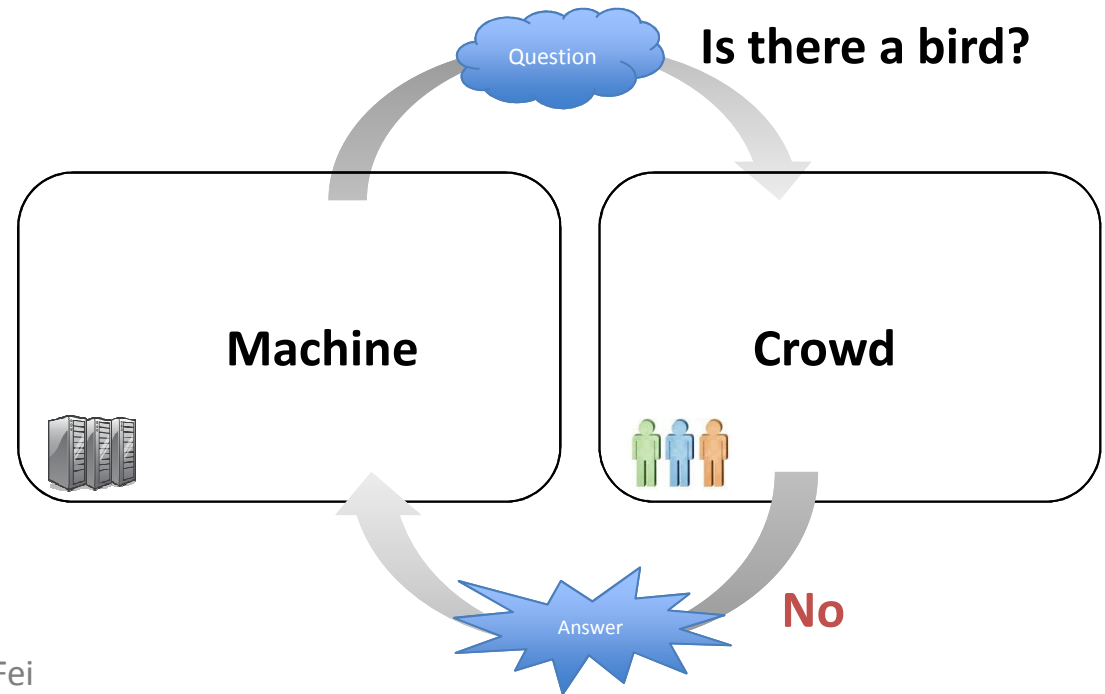
Table	Chair	Horse	Dog	Cat	Bird
+	+	-	-	-	?



# Naïve approach: ask for each object



Table	Chair	Horse	Dog	Cat	Bird
+	+	-	-	-	-



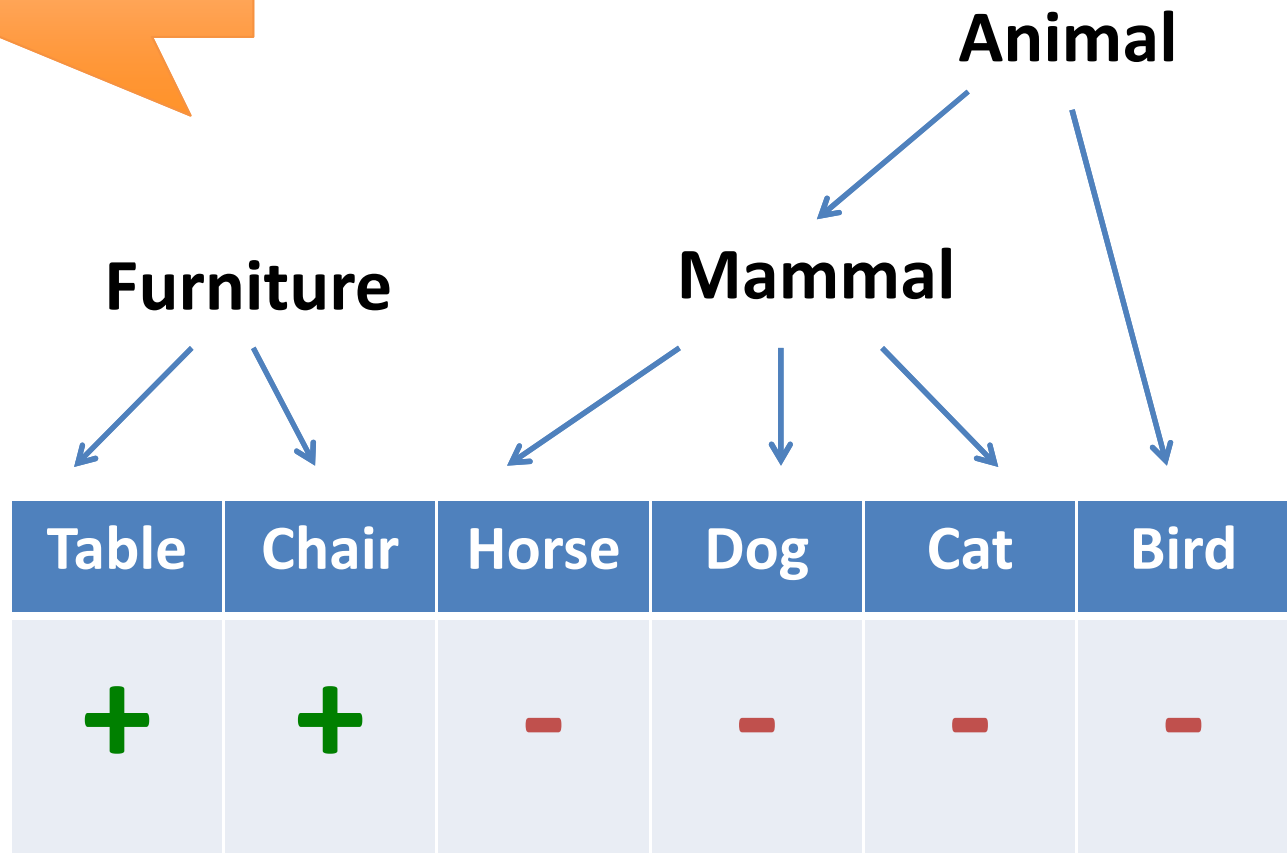
# Naïve approach: ask for each object

Cost:  $O(NK)$  for  $N$  images and  $K$  objects



Table	Chair	Horse	Dog	Cat	Bird
+	+	-	-	-	-
+	-	-	-	+	-
+	+	-	-	-	-

# Hierarchy



# Hierarchy

Furniture

Animal

Mammal

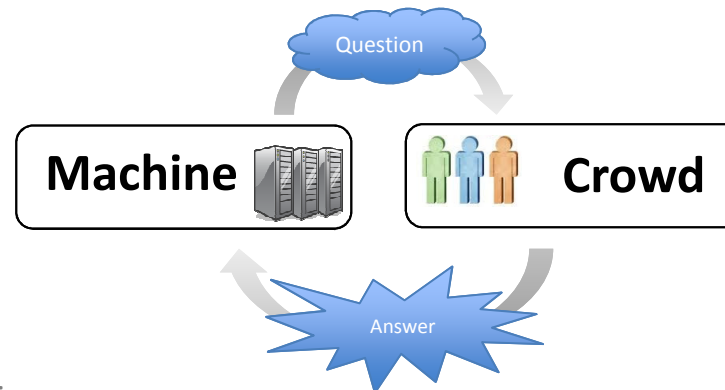
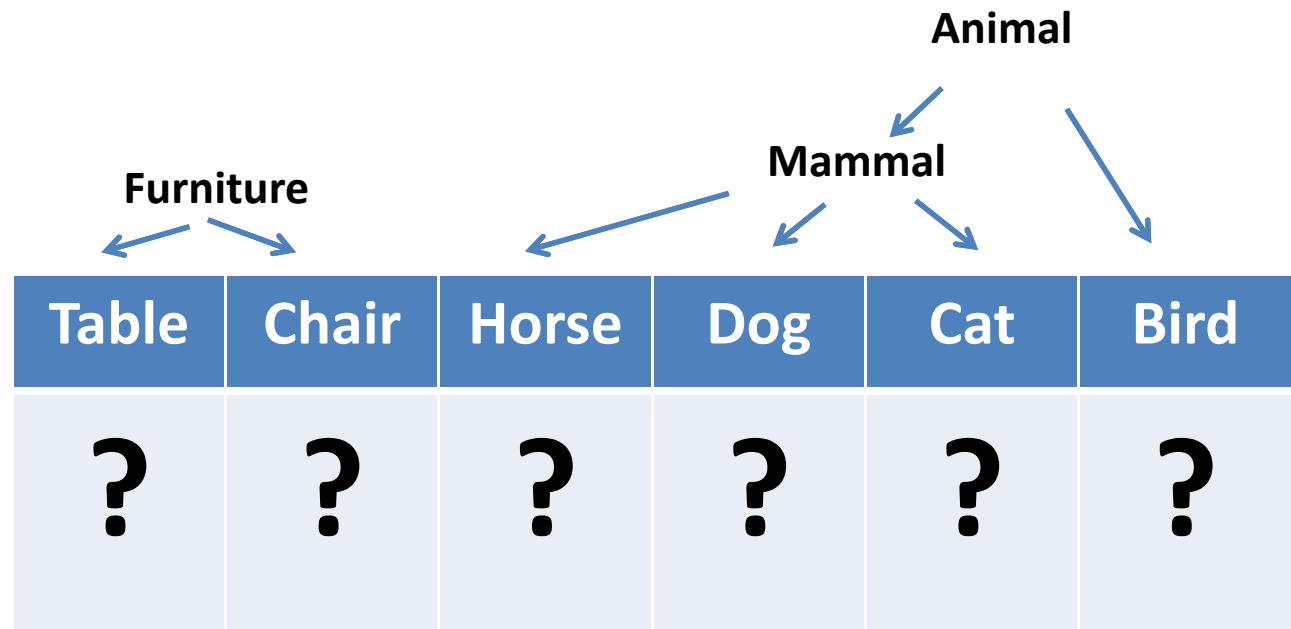


Table	Chair	Horse	Dog	Cat	Bird
+	+	-	-	-	-
+	-	-	-	+	-
+	+	-	-	-	-

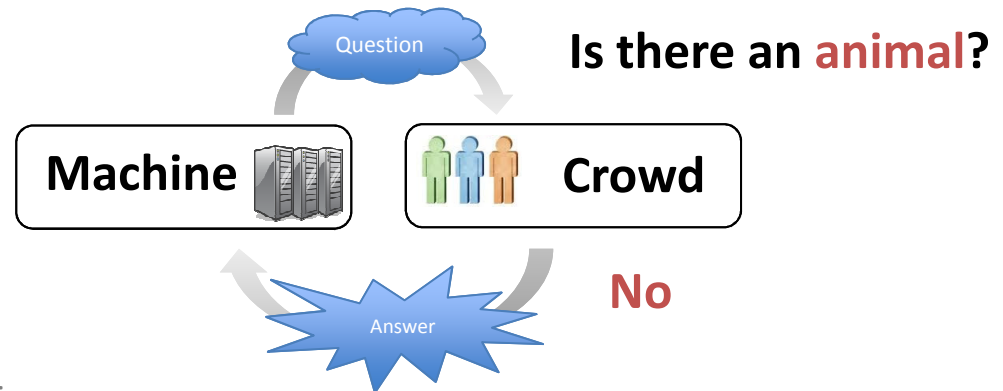
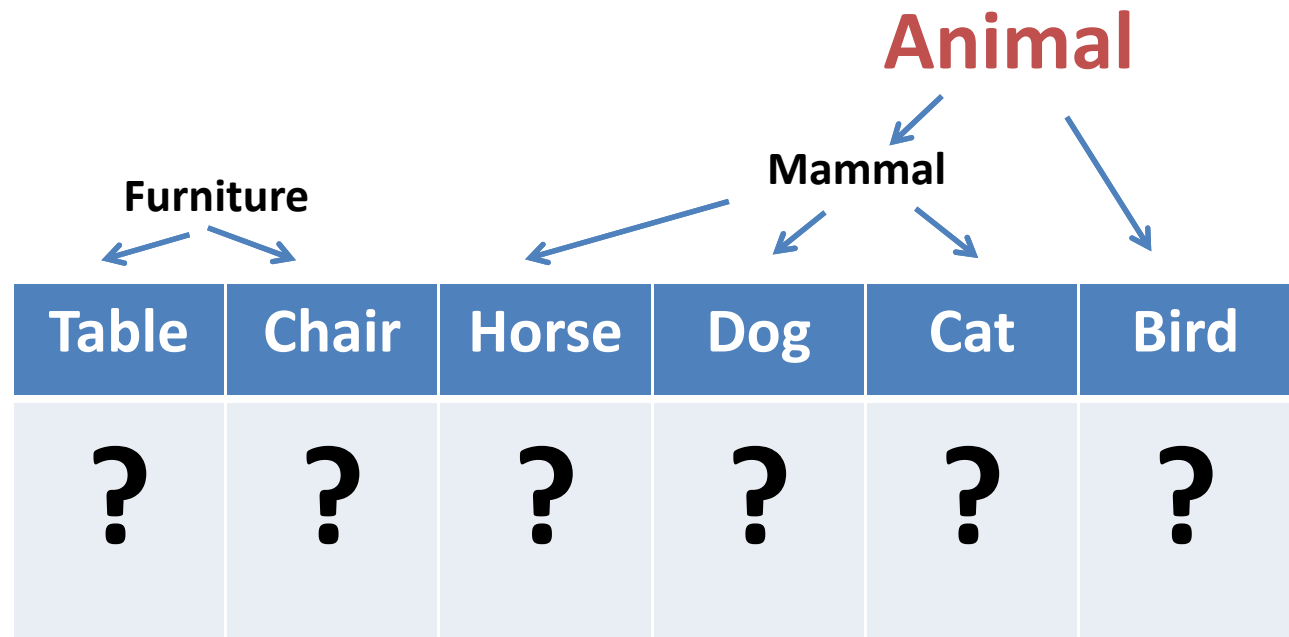
Correlation

Sparsity

# Better approach: exploit label structure



# Better approach: exploit label structure



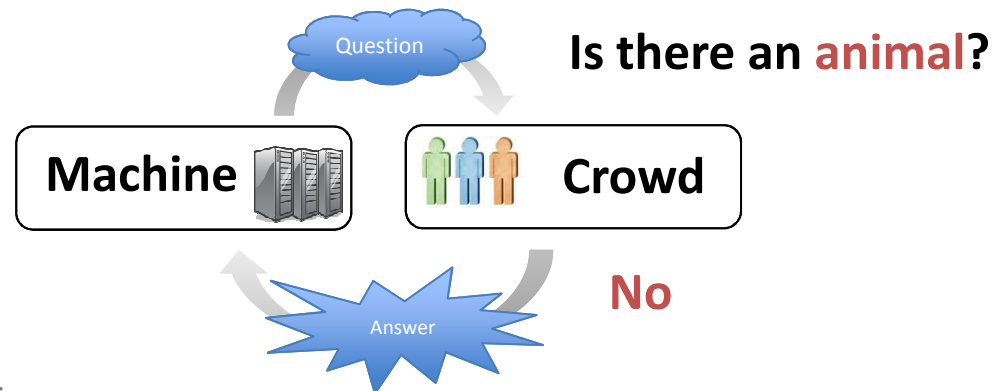
# Better approach: exploit label structure



**Animal**

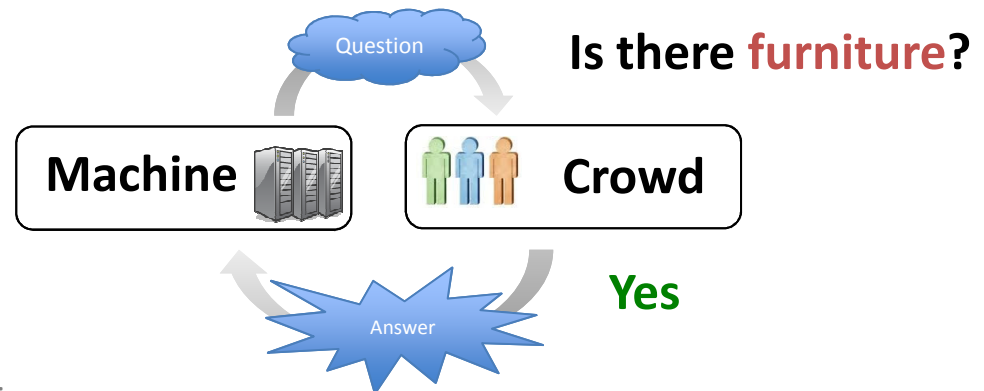
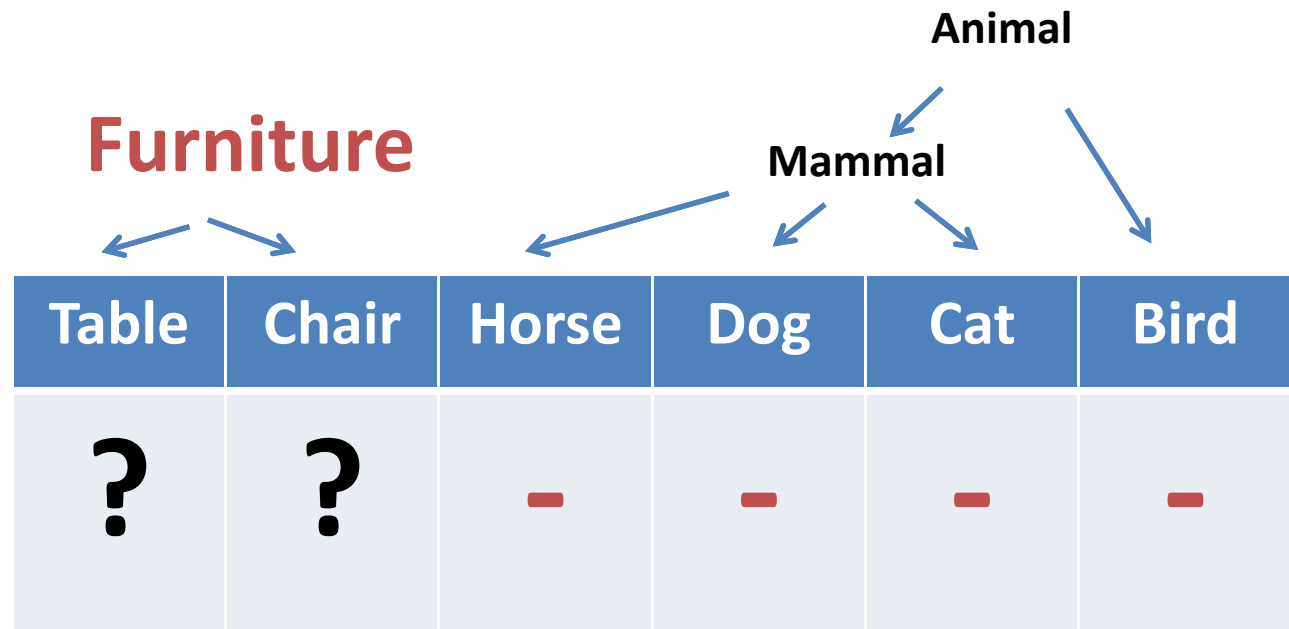
Furniture      Mammal

Table	Chair	Horse	Dog	Cat	Bird
?	?	-	-	-	-

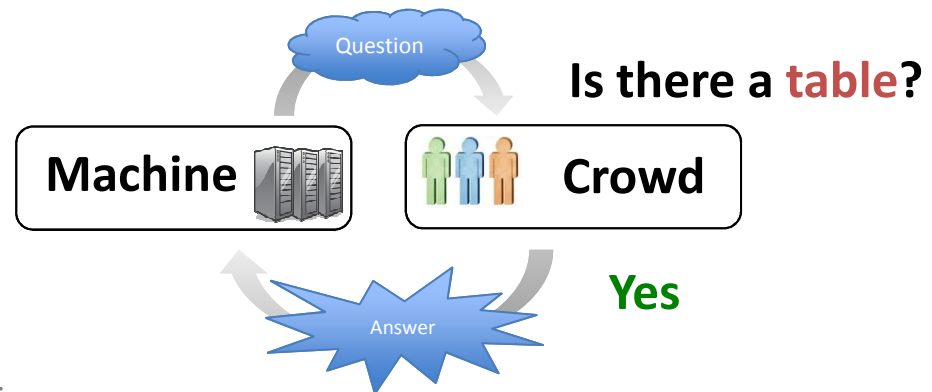
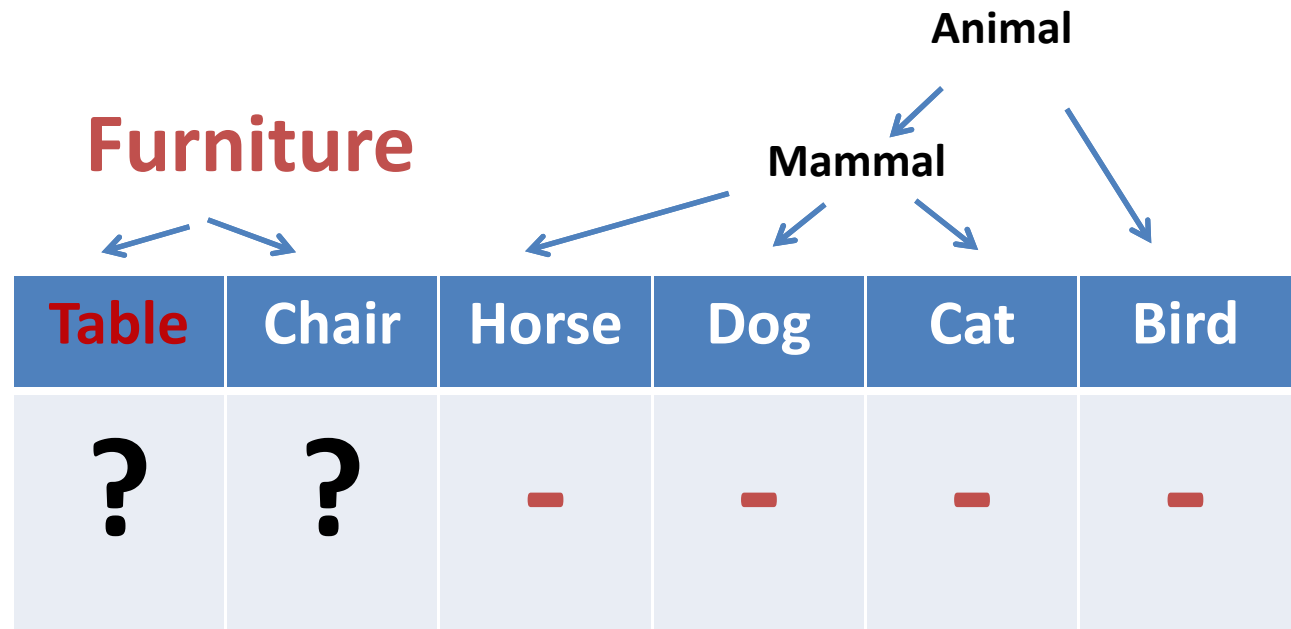




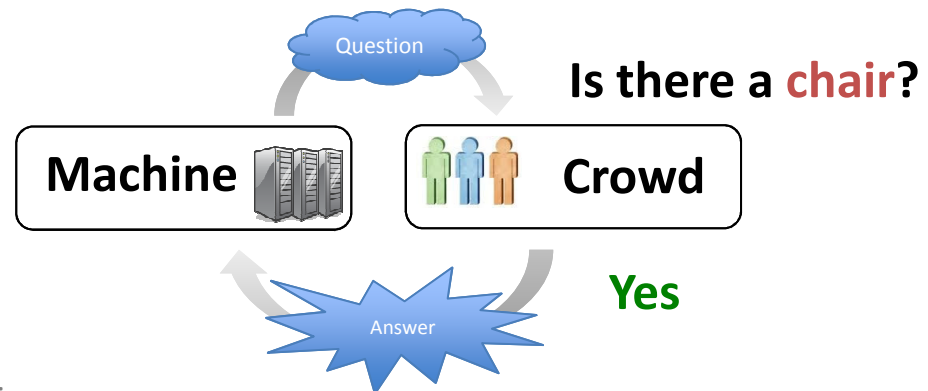
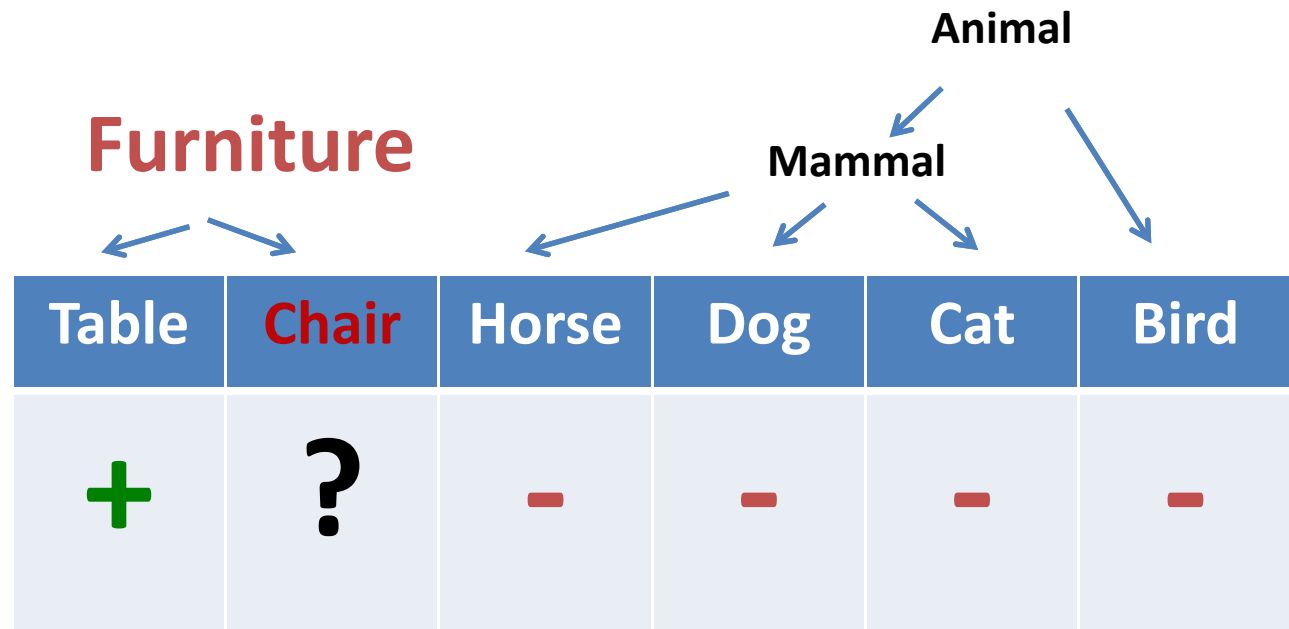
# Better approach: exploit label structure



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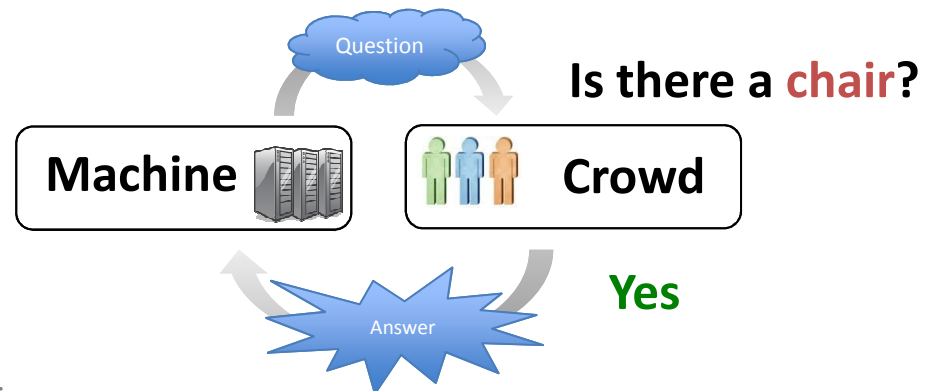


**Furniture**

**Animal**

**Mammal**

Table	Chair	Horse	Dog	Cat	Bird
+	+	-	-	-	-



# Selecting the Right Question

## Goal:

Get as much **utility** (new labels) as possible,  
for as little **cost** (worker time) as possible,  
given a desired level of **accuracy**

# Accuracy constraint

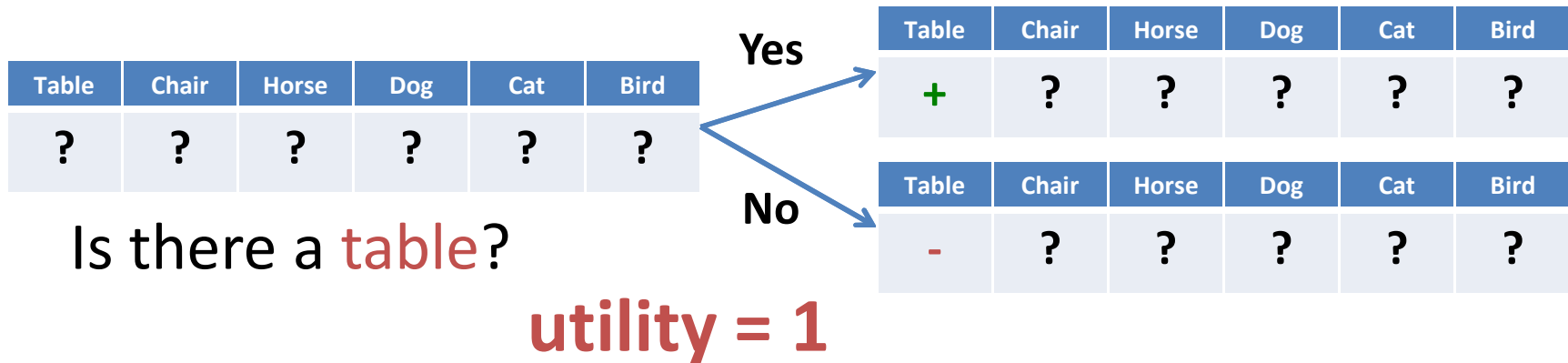
- User-specified accuracy threshold, e.g., 95%
- Majority voting assuming uniform worker quality
  - [GAL: Sheng, Provost, Ipeirotis KDD '08]
- Might require only one worker, might require several based on the task

# Cost: worker time (time = money)

expected human time to get an answer with 95% accuracy

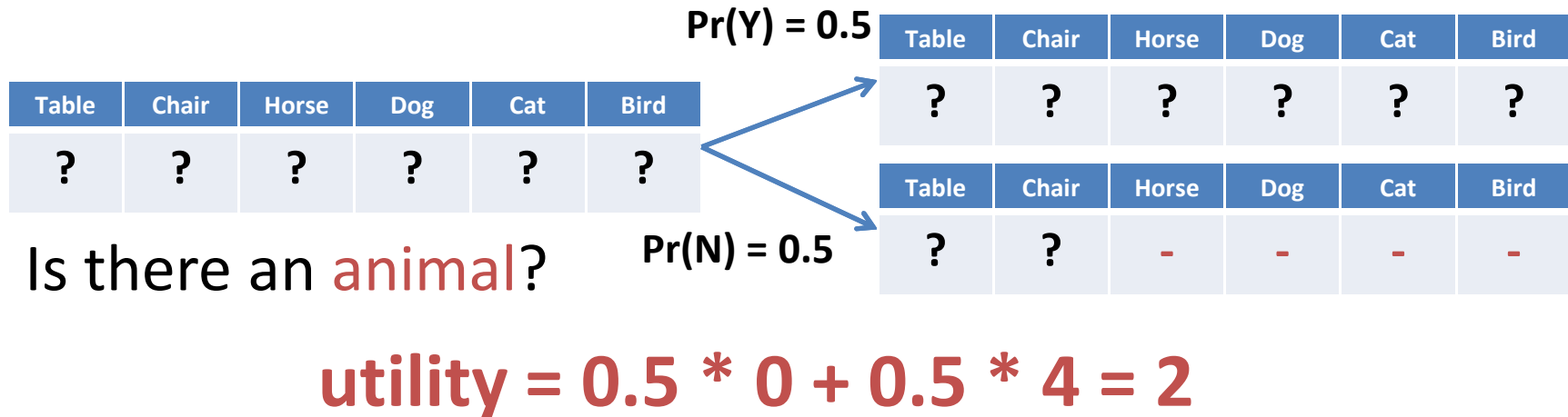
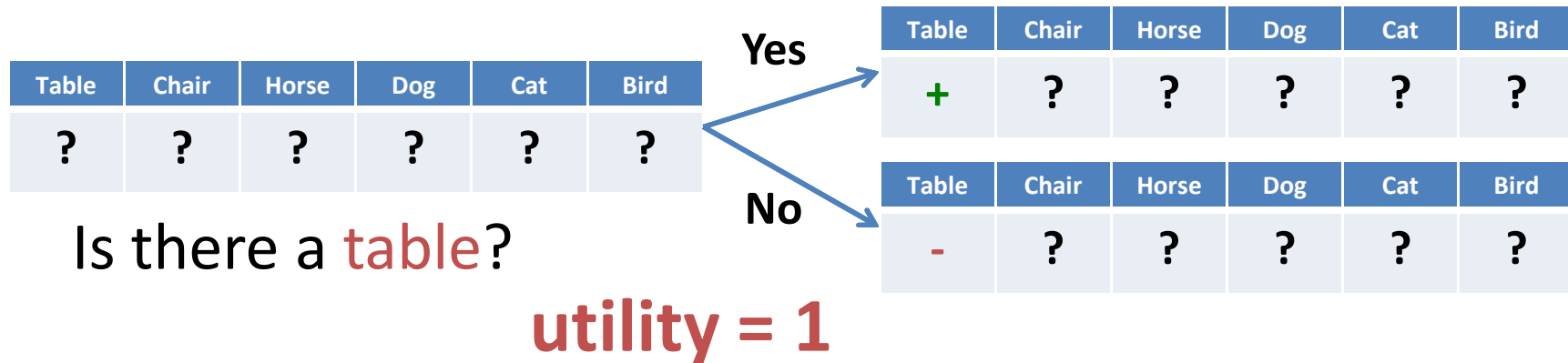
Question (is there ...)	Cost (second)
a thing used to open cans/bottles	14.4
an item that runs on electricity (plugged in or using batteries)	12.6
a stringed instrument	3.4
a canine	2.0

# Utility: expected # of new labels





# Utility: expected # of new labels



# Selecting the Right Question

Pick the question with the most labels per second

Query: Is there a...	Utility (num labels)	Cost (worker time in secs)	Utility-Cost Ratio (labels per sec)
mammal with claws or fingers	12.0	3.0	4.0
living organism	24.8	7.9	3.1
mammal	17.6	7.4	2.4
creature without legs	5.9	2.6	2.3
land or avian creature	20.8	9.5	2.2

# Results

- Dataset: 20K images from ImageNet Challenge 2013.
- Labels: 200 basic categories (dog, cat, table...),  
64 internal nodes in hierarchy



# Results

- Dataset: 20K images from ImageNet Challenge 2013.
- Labels: 200 basic categories (dog, cat, table...), 64 internal nodes in hierarchy
- Setup:
  - 50-50 training test split
  - Estimate parameters on training, simulate on test
  - Future work: online estimation

# Results: accuracy

Annotating 10K images with 200 objects

Accuracy Threshold per question (parameter)	Accuracy (F1 score) Naïve approach	Accuracy (F1 score) Our approach
0.95	99.64 (75.67)	99.75 (76.97)
0.90	99.29 (60.17)	99.62 (60.69)

# Results: cost

Annotating 10K images with 200 objects

Accuracy <b>Threshold</b> per question (parameter)	<b>Cost saving</b> (our approach compared to naïve approach)
0.95	<b>3.93x</b>
0.90	<b>6.18x</b>

# Results: cost

Annotating 10K images with 200 objects

Accuracy <b>Threshold</b> per question (parameter)	<b>Cost saving</b> (our approach compared to naïve approach)
0.95	<b>3.93x</b>
0.90	<b>6.18x</b>

6 times more  
labels per  
second

# Conclusions

Speeds up crowdsourced multi-label annotation by exploiting the structure and distribution of labels.  
Could be a bargain for you!

