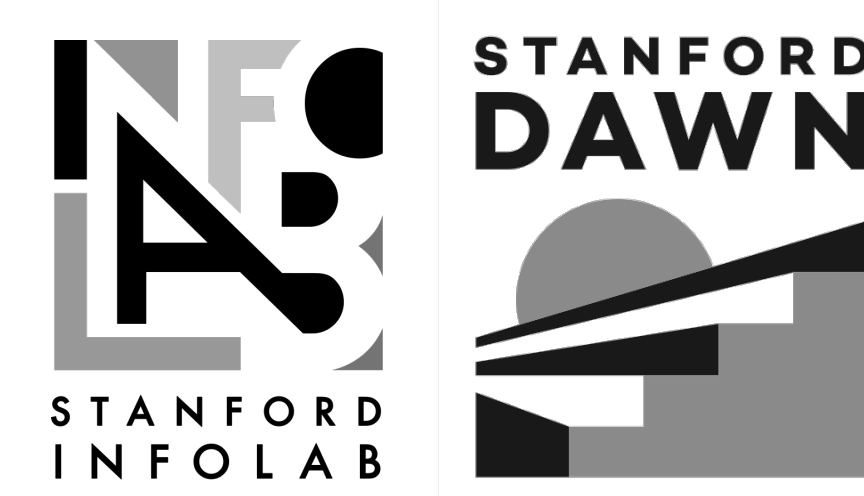


Inferring Generative Model Structure with Static Analysis

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Summary

- Generative Models to Label Training Data**
Use generative models to combine sources of weak supervision to assign noisy labels
- Complex Dependencies among Sources**
Sources of labels are rarely independent
- Inferring Model Structure**
Use static analysis to infer dependencies and encode in generative model structure

```
def λ1(P.y):  
    if P.y['person'] >= P.y['bike']:  
        return True  
    else:  
        return False
```

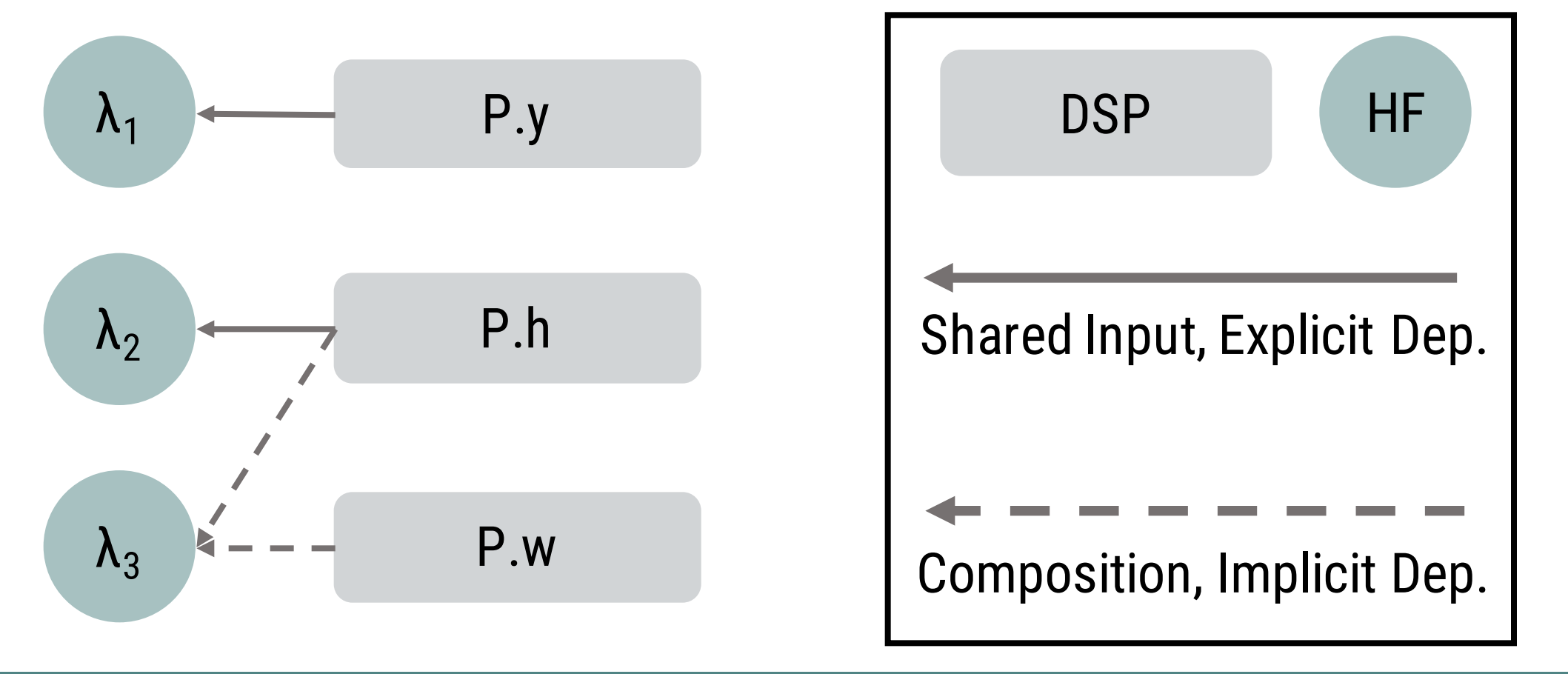
```
def λ2(P.h):  
    if P.h['person'] >= P.h['bike']:  
        return True  
    else:  
        return False
```

```
def λ3(P.area):  
    if P.area['person'] <= 2 * P.area['bike']:  
        return True  
    else:  
        return False
```

Theoretical Results

- Learning Dependencies**
Learning k-degree dependencies among n heuristics requires $O(n^{k-1} \log n)$ samples
- Inferring Dependencies**
Analyzing the code can infer the dependencies among heuristics without data

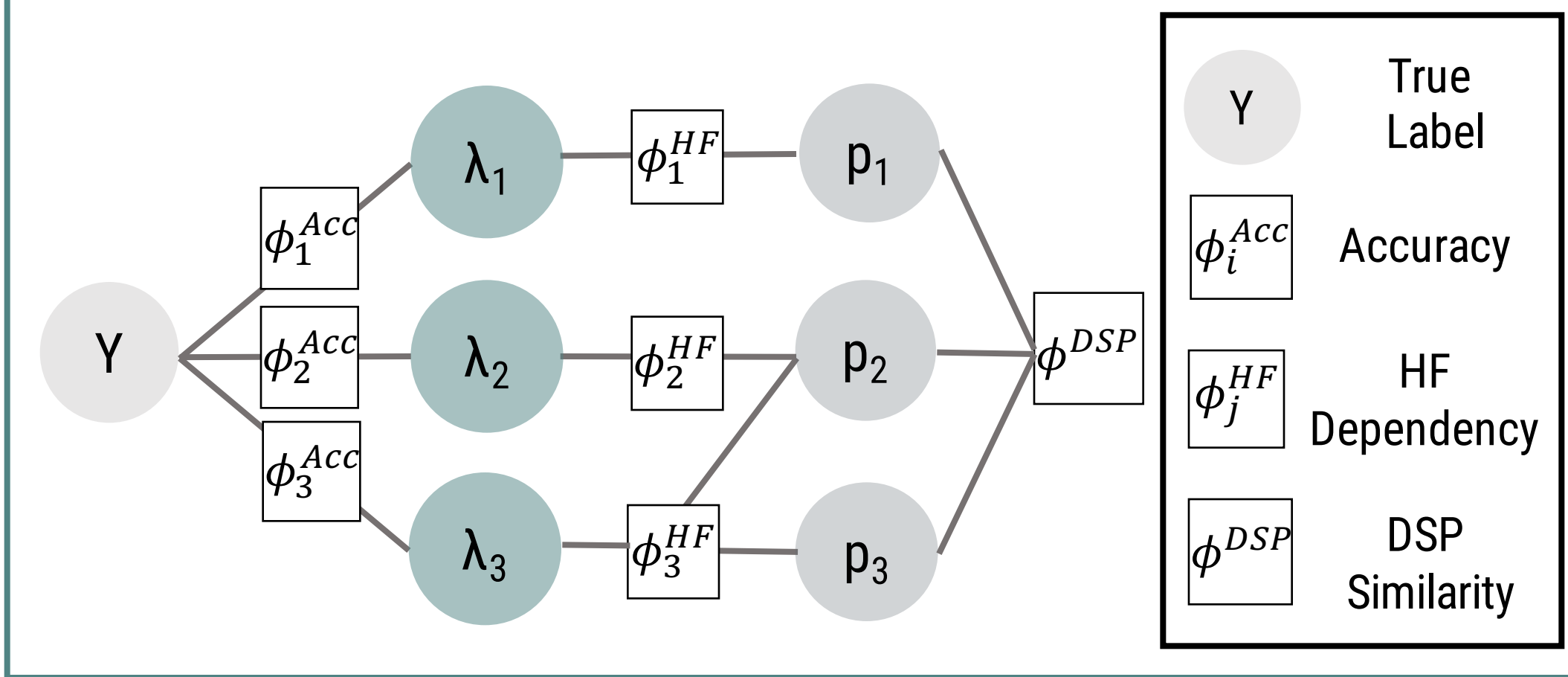
Given dependencies, learning heuristic accuracies requires $O(n \log n)$ samples



Experimental Results

| Application | Model | Improvement Over | | | |
|---------------|-----------|------------------|-------|-----------|--------|
| | | MV | Indep | Learn Dep | FS |
| Visual Genome | GoogLeNet | 7.49* | 2.90* | 2.90* | -0.74* |
| ActivityNet | VGGNet+LR | 6.23* | 3.81* | 3.81* | -1.87* |
| Bone Tumor | LR | 5.17 | 3.57 | 3.06 | 3.07 |
| Mammogram | GoogLeNet | 4.62 | 1.11 | 0 | -0.64 |

- * reports F1 scores, rest in accuracy (%)
- Inferring dependencies outperforms learning dependencies
 - Outperforms fully supervised model with additional noisy training labels



Heuristic Structure

- Domain Specific Primitives (DSPs)**
Interpretable characteristics of raw data
- Heuristic Functions (HFs)**
Programmatic rules that output noisy labels

Static Analysis

- Shared Input** Sharing primitives as inputs leads to explicit dependencies
- Compositions:** Primitives composed of others can lead to implicit dependencies

Statistical Modeling

- HF Dependency** Represents the dependencies found using static analysis
- DSP Similarity** Represents the learned correlations among the DSPs