State of the art of unsupervised learning and where it is being currently used

19fall A2 Group 4

Zhou: Future Languages in Machine Learning (1)

TABLE I
COMPARISON OF LANGUAGE FEATURES

	Python	Swift	Julia	Rust
Type	dynamic, duck	static, strong	dynamic, nominal	static, strong, nominal
Compiling	Interpret	LLVM	JIT, can build executable	LLVM
Syntax Style	-	Like Python	Fortran, Matlab	custom, ALGOL
GC	Yes, Interpret	Yes, ARC	Yes, JIT	No, but Memory Safe
Unsafe Ops	No	No by default	No by default	No
Performance	Low	High	High	Top Level
Parallel (CPU)	Bad Support	Support	Support by Native	Support
C Interop	Yes	Yes	Both C and Fortran	Yes
Python Interop	-	Yes	Yes	No
Mobile & Embedding	Poor	Good	Poor	Good

Zhou: Future Languages in Machine Learning (2)

TABLE II
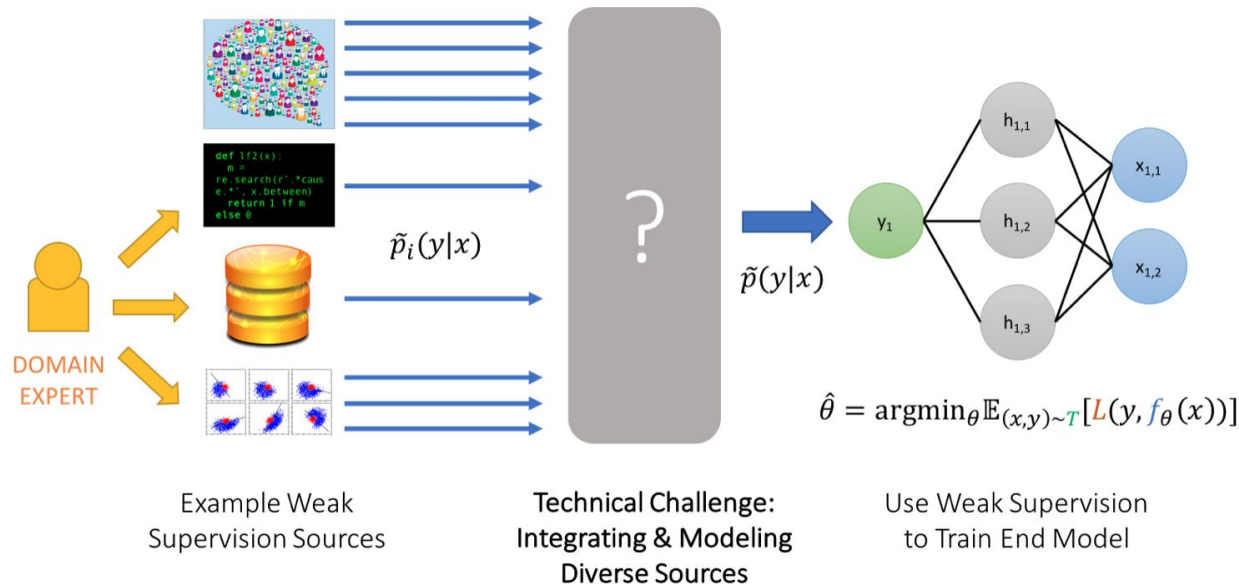### COMPARISON OF COMMUNITY FEATURES

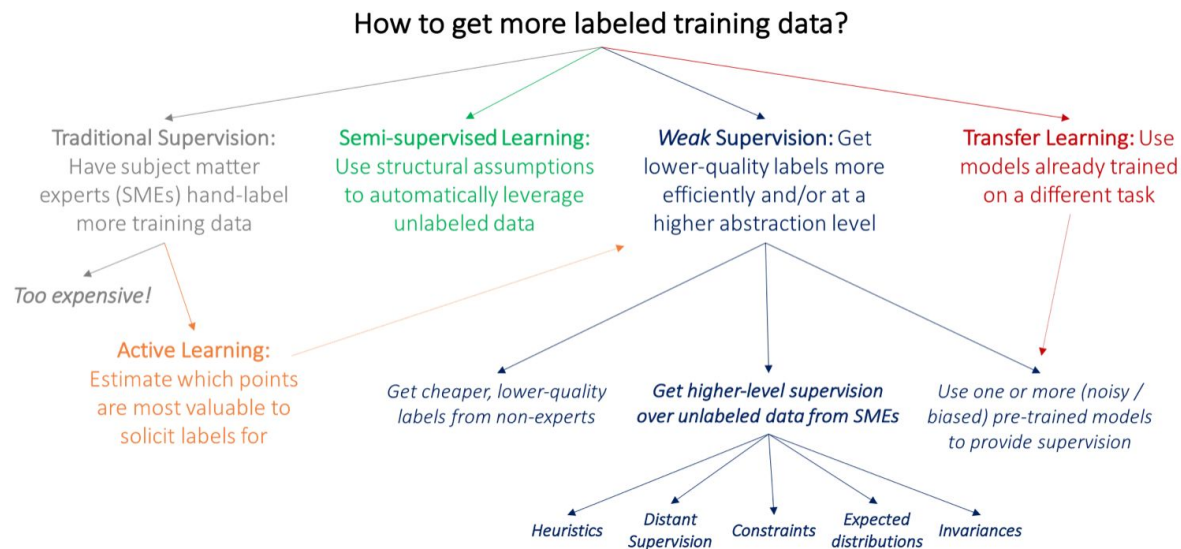|	Python	Swift	Julia	Rust
Target	General	General	Scientific Computing	System / General
License	PSFL	Apache 2.0	MIT (core)	MIT
Learning Difficulty	Low	Middle	Middle	High
Mainstream DL Lib	plenty	TensorFlow	Flux.jl	leaf / TensorFlow bind

Zhou: Future Languages in Machine Learning (3)

For ML researchers and developers, there are a lots of tool sets available to simplify their works, include:

- *Scientific Computing*: Numpy, Scipy
- *Hardware Accelerator*: CUDA, Vulkan support
- *General ML*: Sci-Kit Learn
- *Deep Learning*: TensorFlow, PyTorch
- *Data Processing*: Pandas
- *Various Algorithms Set*: OpenCV, plenty of scripts available on GitHub
- *Visualization*: Matplotlib, Seaborn

Liu: Unsupervised Learning & Snorkel (1)

Example Weak
Supervision Sources

Technical Challenge:
Integrating & Modeling
Diverse Sources

Use Weak Supervision
to Train End Model

Liu: Unsupervised Learning & Snorkel (2)

How to get more labeled training data?

Traditional Supervision: Have subject matter experts (SMEs) hand-label more training data

Too expensive!

Active Learning: Estimate which points are most valuable to solicit labels for

Semi-supervised Learning: Use structural assumptions to automatically leverage unlabeled data

Weak Supervision: Get lower-quality labels more efficiently and/or at a higher abstraction level

Get cheaper, lower-quality labels from non-experts

Get higher-level supervision over unlabeled data from SMEs

Heuristics   *Distant Supervision*   *Constraints*   *Expected distributions*   *Invariances*

Transfer Learning: Use models already trained on a different task

Use one or more (noisy / biased) pre-trained models to provide supervision

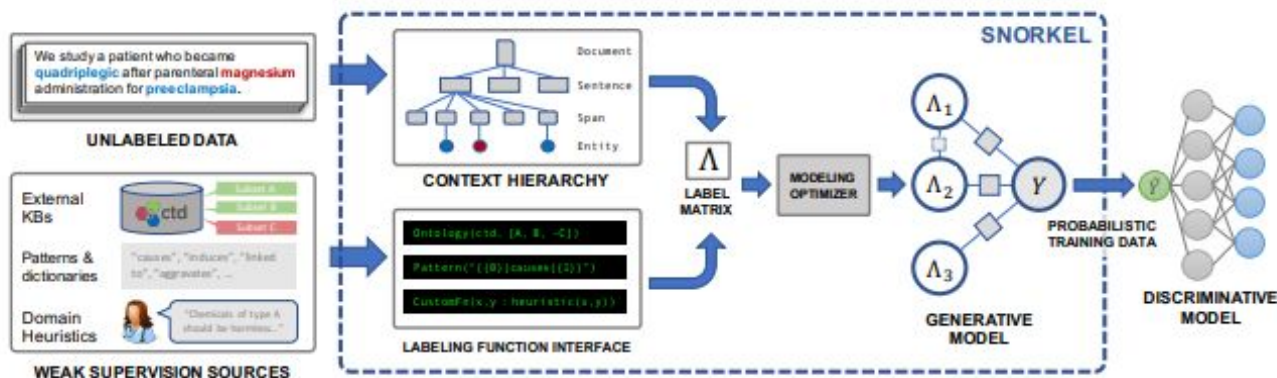# Liu: Unsupervised Learning & Snorkel (3)

Figure 2: An overview of the Snorkel system. (1) SME users write *labeling functions (LFs)* that express weak supervision sources like distant supervision, patterns, and heuristics. (2) Snorkel applies the LFs over unlabeled data and learns a generative model to combine the LFs' outputs into probabilistic labels. (3) Snorkel uses these labels to train a discriminative classification model, such as a deep neural network.

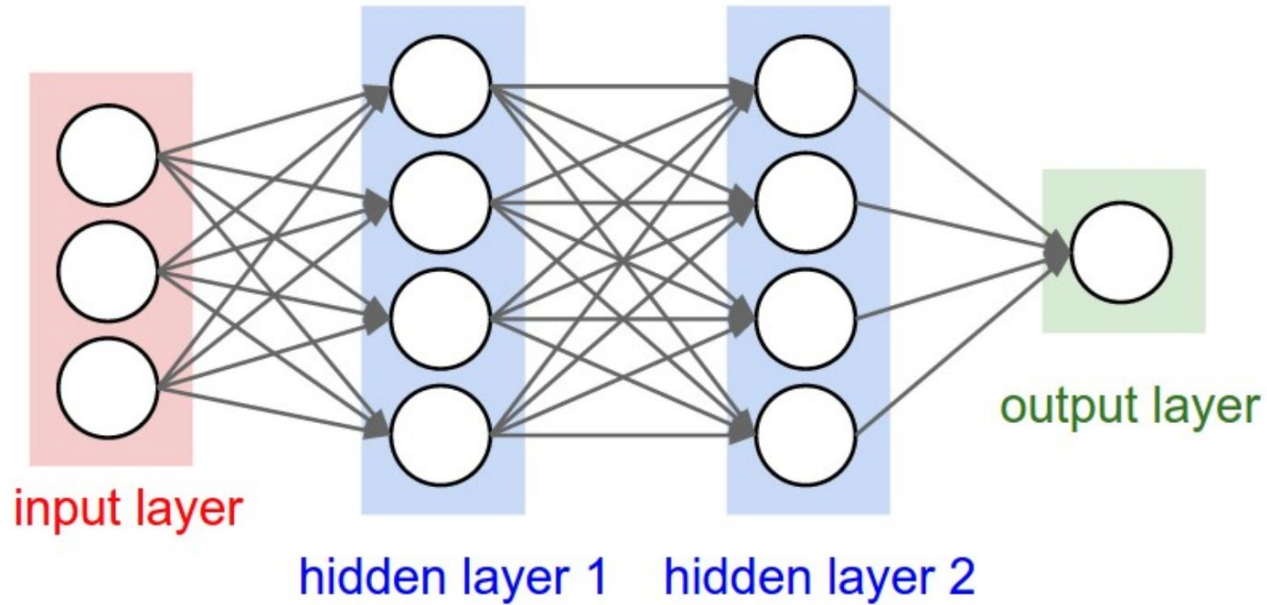# Liu: Unsupervised Learning & Snorkel (4)
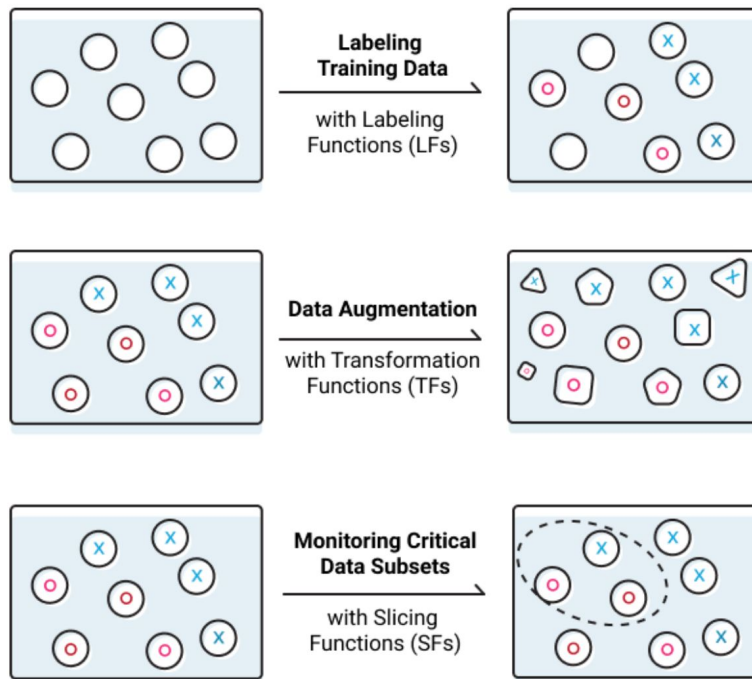
Chen: Machine Learning and Artificial Intelligence (1)
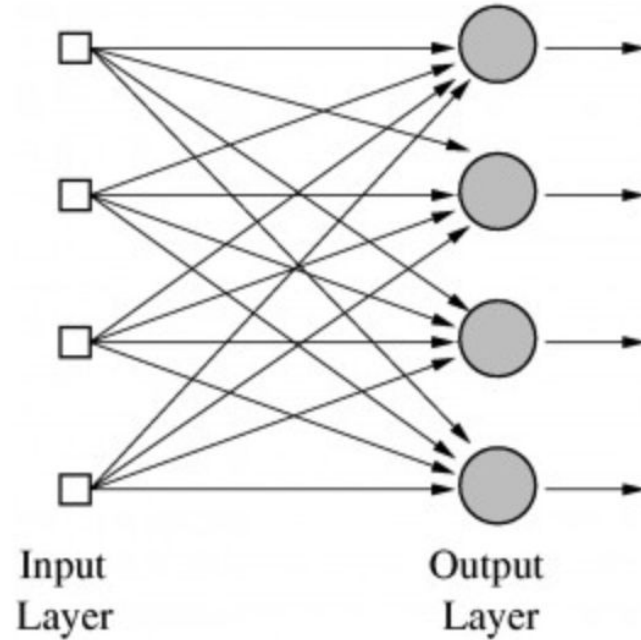
A neural net with multiple outputs.

Chen: Machine Learning and Artificial Intelligence (2)

Zhang: State of the art of object segmentation methods based on machine learning algorithms

Article Topic	Summary
Extracting Key Segments of Videos	An adaptive latent structural support vector machine model
Brain Tumor Detection	An improved gamma distribution-based machine-learning approach
cell/nucleus segmentation	A novel contour-seed pairs learning-based framework
Segment generic objects	An end to end learning framework

JAIN: A survey of Dimensionality Reduction Technique
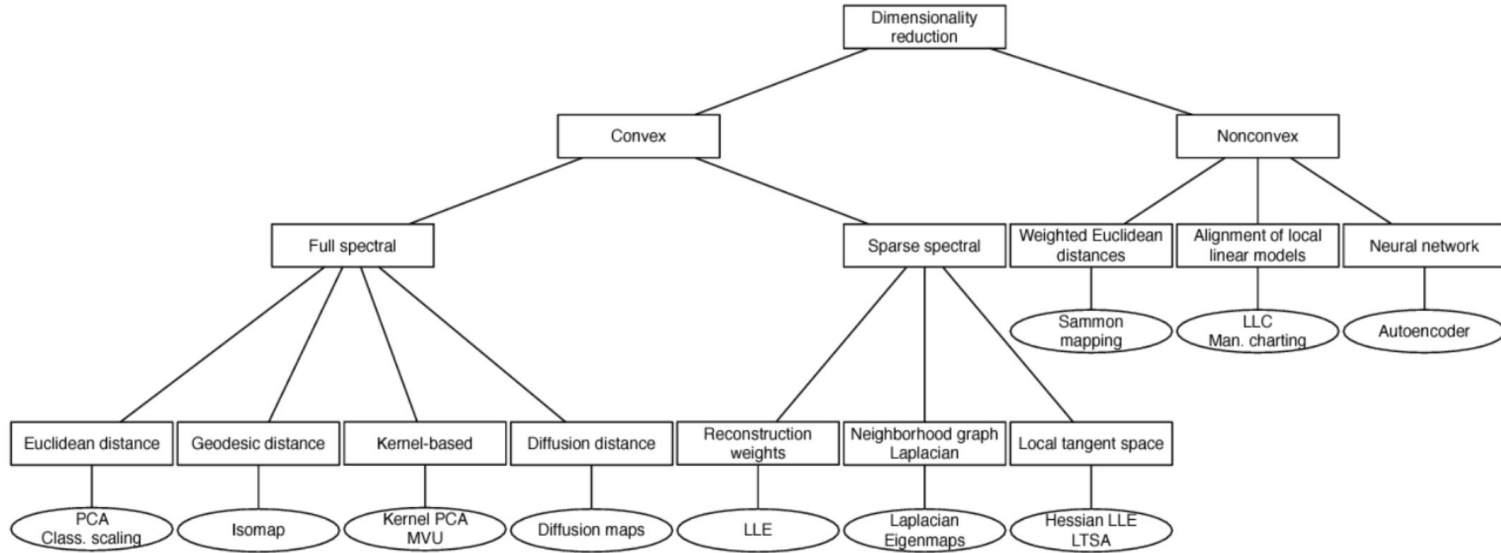

Fig 1. Taxonomy of Dimensionality Reduction Techniques [3]

Krishna: Multi-View 3D Object detection network for autonomous driving (1)

It is about detecting 3D objects using LIDAR and RGB. Their method did better than most state-of-the art technology cause they used various techniques like, extracting deep features using deep fusion (better than early fusion or late fusion), using both LIDAR and RGB as input, using **eagle eye** from LIDAR, the foundation of this model being VGG, **using a regression model** to identify the 3D objects by predicting the corners using the fused deep features.

Krishna: Multi-View 3D Object detection network for autonomous driving (2)

However, they just tested their model **on a single KITTI dataset**, thought its a benchmark, **more comparison was not provided,** also they proposed this model for autonomous vehicle problem, but they did **not mention any metrics** related to timing of the model because that's really important for autonomous vehicles problem. They also have a limitation when it comes to multimodal data, i.e data from both LIDAR instrument and a camera. The recommendation on adoption of this model would be to consider the required hardware for the model to collect the inputs, its timing analysis, and also more metrics regarding the performance of this model against multiple datasets just to make sure there was no overfitting, before adopting this model.