



CS 329P: Practical Machine Learning (2021 Fall)

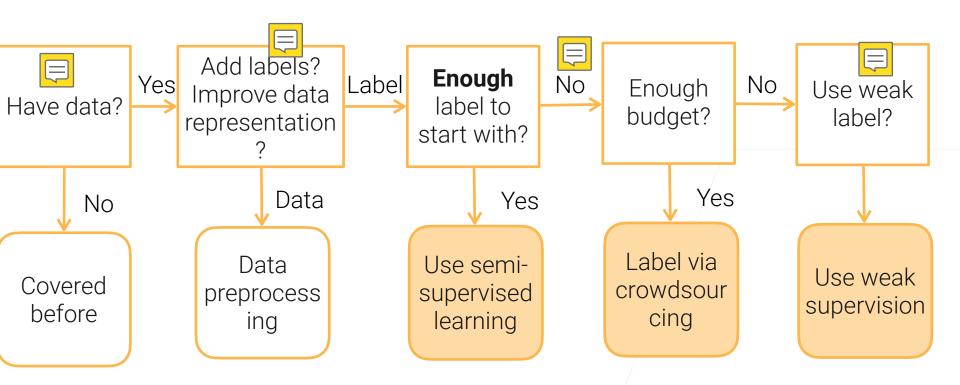
# 1.4 Data Labeling

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https://c.d2l.ai/stanford-cs329p

### Flow Chart for Data Labelling





# Semi-Supervised Learning (SSL)

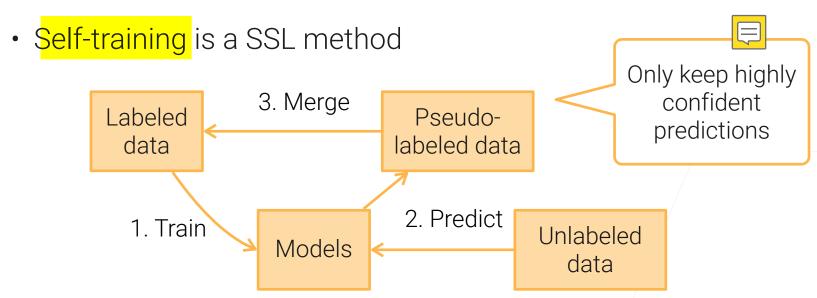


- Focus on the scenario where there is a small amount of labeled data, along with large amount of unlabeled data
- Make assumptions on data distribution to use unlabeled data
  - Continuity assumption: examples with similar features are more likely to have the same label
  - Cluster assumption: data have inherent cluster structure, examples in the same cluster tend to have the same label
  - Manifold assumption: data lie on a manifold of much lower dimension than the input space

# **Self-training**







- We can use expensive models
- Deep neural networks, model ensemble/bagging

# **Label through Crowdsourcing**





- ImageNet labeled millions of images through Amazon
   Mechanical Turk. It took several years and millions dollars to
   build
- According to Amazon SageMaker Ground Truth, the estimated price of using Amazon Mechanical Turk:

Image/text classification	\$0.012 per label
Bounding box	\$0.024 per box
Semantic segmentation	\$0.84 per image

### Challenges





- Simplify user interaction: design easy tasks, clear instructions and simple to use interface
  - Needs to find qualified workers for complex jobs (e.g. label medical images)
- Cost: reduce #tasks X #time per task sent to labelers
- Quality control: label qualities generated by different labelers vary



#### **User interaction**



• Example of user instruction and labeling task (MIT Place365)





### Reduce #tasks: Active Learning





- Focus on same scenario as SSL but with human in the loop
  - Self training: Model helps propagate labels to unlabeled data
  - Active learning: Model select the most "interesting" data for labelers



#### Uncertainty sampling



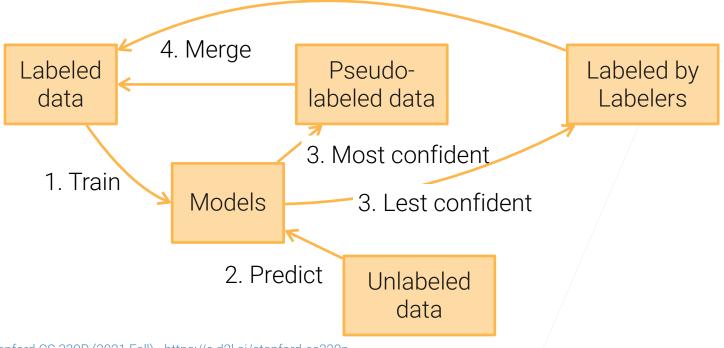
- Select examples whose predictions are most uncertain
- The highest class prediction score is close to random (1/n)
- Query-by-committee
  - Trains multiple models and select samples that models disagree with

# Active Learning + Self-training





These two methods are often used together



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### **Quality Control**



• Labelers make mistakes (honest or not) and may fail to understand the instructions











- Simplest but most expensive: sending the same task to multiple labelers, then determine the labelers by majority voting
  - Improve: repeat more for controversial examples, prune low-quality labelers

## Weak Supervision





- Semi-automatically generate labels
  - Less accurate than manual ones, but good enough for training
- Data programming:



- Domain specific heuristics to assign labels
- Keyword search, pattern matching, third-party models
- E.g. rules to check if YouTube comments are spam or ham

```
def check_out(x):
    return SPAM if "check out" in x.lower() else ABSTAIN

def sentiment(x):
    return HAM if sentiment_polarity(x) > 0.9 else ABSTAIN

def short_comment(x):
    return HAM if len(x.split()) < 5 else ABSTAIN</pre>
```



## Data Labeling for Self-driving Car



- Tesla and Waymo both have large in-house data labeling teams
- Labels needed: 2D/3D bounding box, image semantic segmentation, 3D laser point cloud annotation, video annotation,...
- Use active learning to identify scenarios which need more data / label
- Use ML algorithms for automatic labeling
- Use simulation to generate perfectly labeled, unlimited data for rare situations

### Summary



Ways to get labels



- Self-training: iteratively train models to label unlabeled data
- Crowdsourcing: leverage global labelers to manually label data
- Data programming: heuristic programs to assign noisy labels
- Alternatively, You could also consider unsupervised/selfsupervised learnings

## Flow chart for data preprocessing



