Stanford University

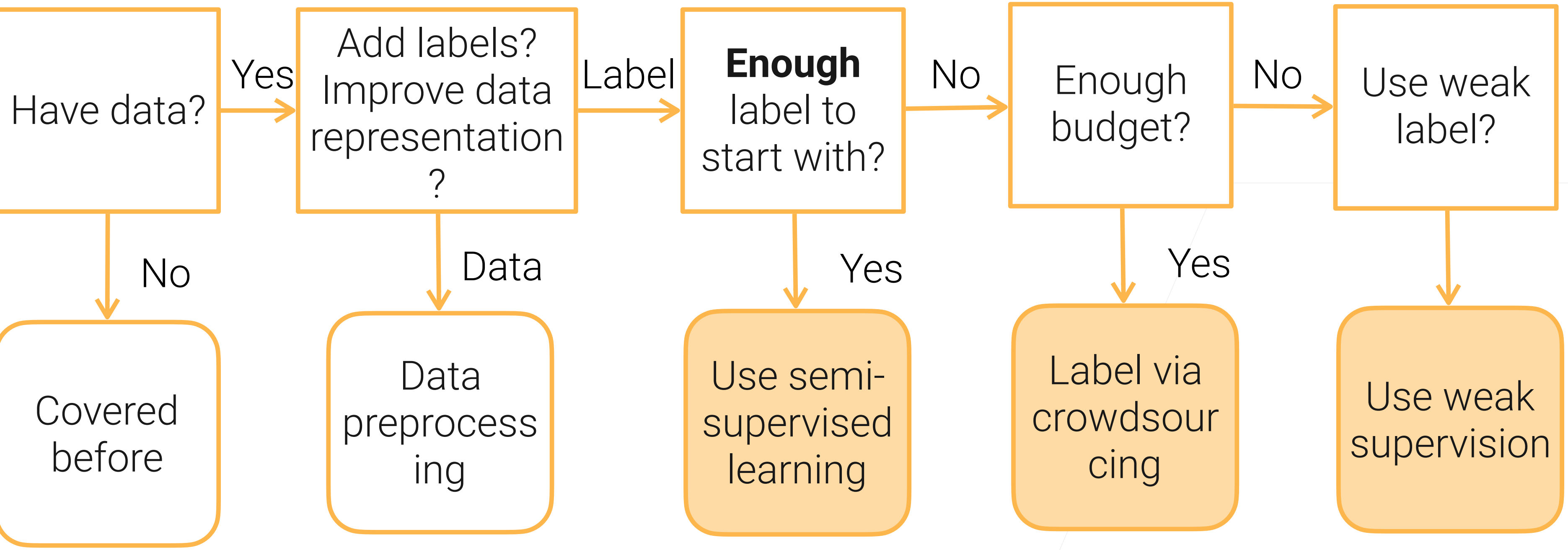
CS 329P : Practical Machine Learning (2021 Fall)

1.4 Data Labeling

Qingqing Huang, Mu Li, Alex Smola

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

Flow Chart for Data Labelling

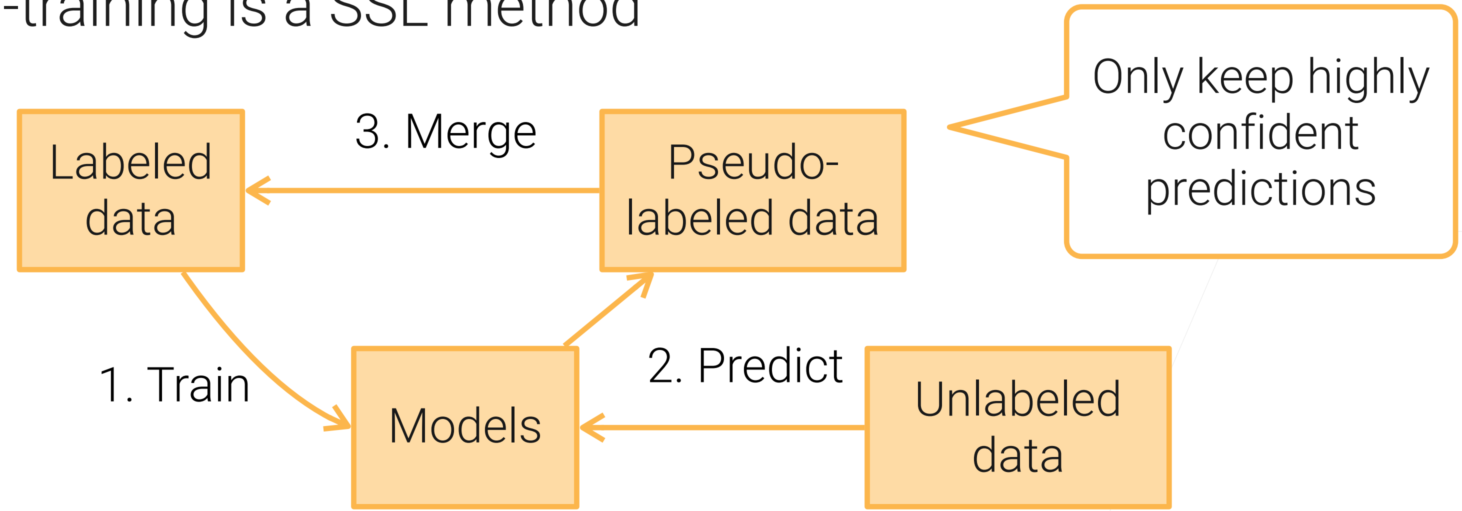


Semi-Supervised Learning (SSL)

- 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

- Self-training is a SSL method



- 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

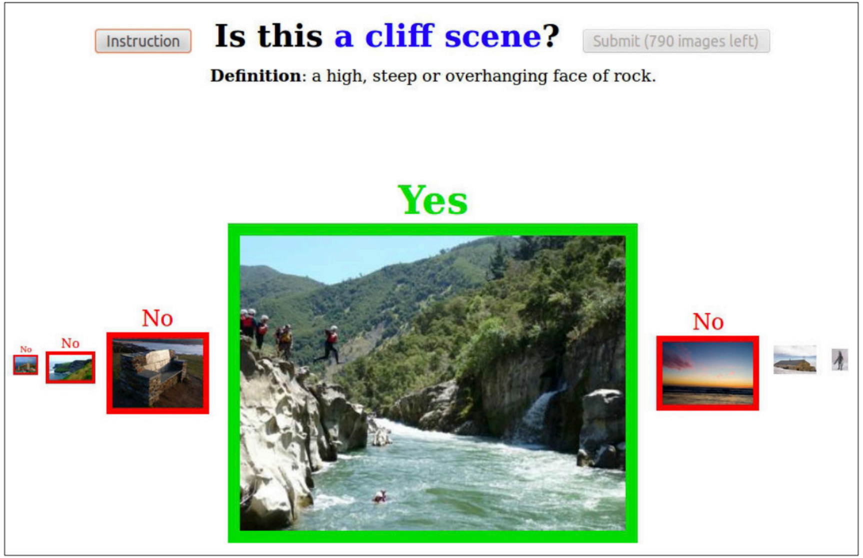
Challenges

- 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)

b)

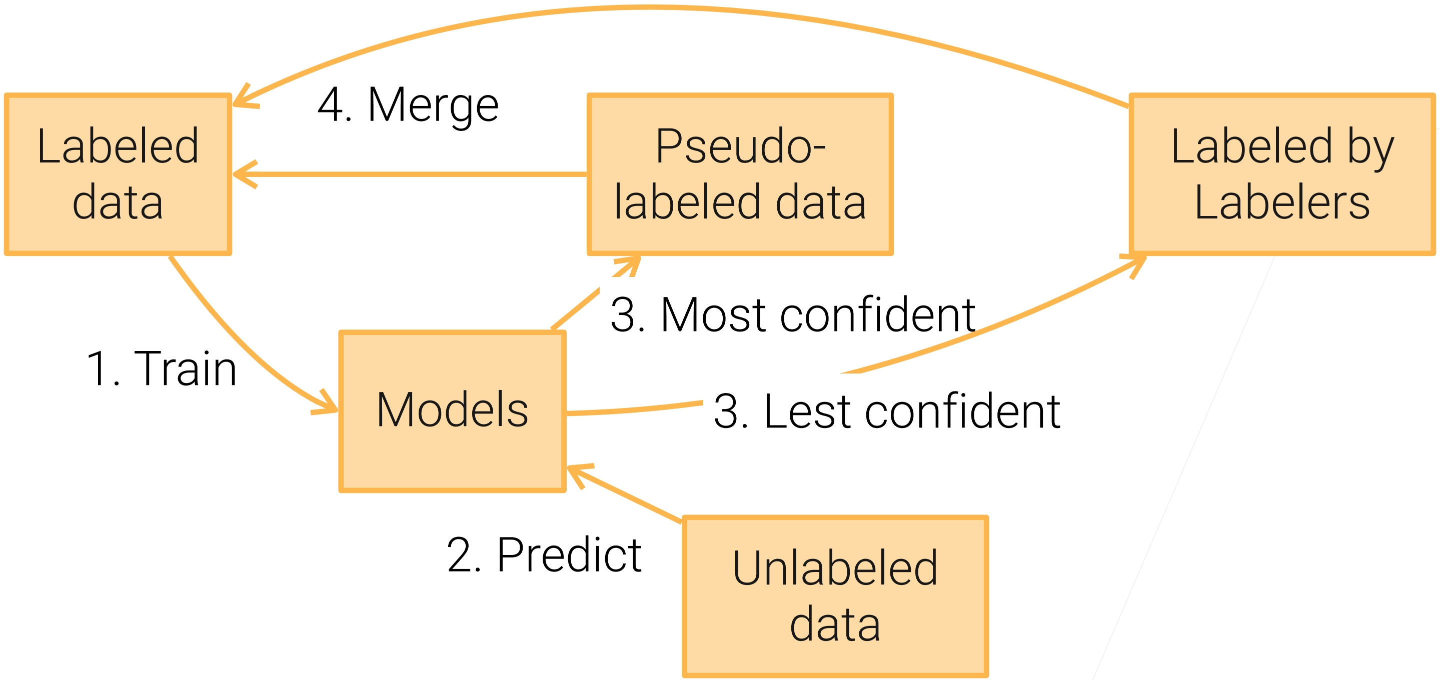


Reduce #tasks: Active Learning

- 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

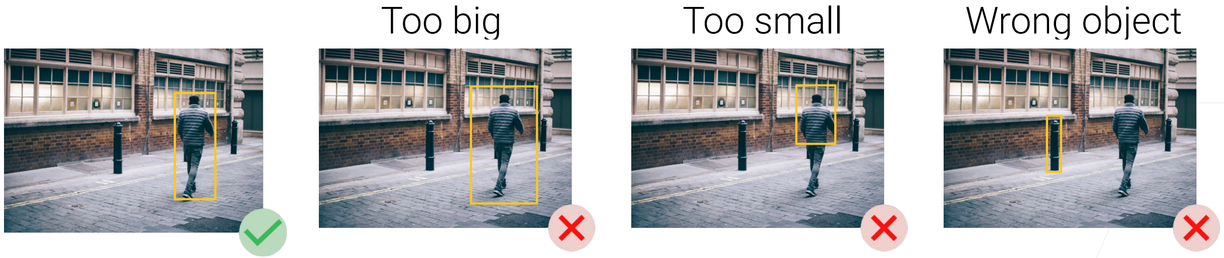
Active Learning + Self-training

- These two methods are often used together



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 label by majority voting
  - Improve: repeat more for controversial examples, prune low-quality labelers

Weak Supervision

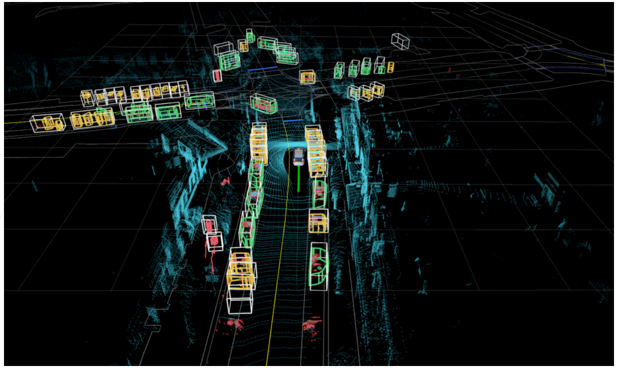
- Semi-automatically generate labels
  - Less accurate than manual ones, but good enough for training
- Data programming:
  - Domain specific heuristics to assign labels
  - Keyword search, pattern matching, third-party models
  - E.g. rules to check if YouTube comments are spam or ham

```python
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
```

Adapted from snorkel.org

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/self-supervised learnings

Flow chart for data preprocessing