DSC291: Machine Learning with Few Labels

Weak/distant supervision

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Recap: Data Augmentation

- Image:
  - *Flip, crop, scale, translation, rotation, mixup, …*
- Text:

Methods	Level	Diversity	Tasks	Related Work
Synonym replacement	Token	Low	Text classification Sequence labeling	Kolomiyets et al. (2011), Zhang et al. (2015a), Yang (2015), Miao et al. (2020), Wei and Zou (2019)
Word replacement via LM	Token	Medium	Text classification Sequence labeling Machine translation	Kolomiyets et al. (2011), Gao et al. (2019) Kobayashi (2018), Wu et al. (2019a) Fadaee et al. (2017)
Random insertion, deletion, swapping	Token	Low	Text classification Sequence labeling Machine translation Dialogue generation	Iyyer et al. (2015), Xie et al. (2017) Artetxe et al. (2018), Lample et al. (2018) Xie et al. (2020), Wei and Zou (2019)
Compositional Augmentation	Token	High	Semantic Parsing Sequence labeling Language modeling Text generation	Jia and Liang (2016) , Andreas (2020) Nye et al. (2020), Feng et al. (2020) Furrer et al. (2020) , Guo et al. (2020)
Paraphrasing	Sentence	High	Text classification Machine translation Question answering Dialogue generation Text summarization	Yu et al. (2018), Xie et al. (2020) Chen et al. (2019), He et al. (2020) Chen et al. (2020c), Cai et al. (2020)
Conditional generation	Sentence	High	Text classification Question answering	Anaby-Tavor et al. (2020), Kumar et al. (2020) Zhang and Bansal (2019), Yang et al. (2020)

Recap: Data Augmentation

- Image:
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- Text:

White-box attack	Token or Sentence	Medium	Text classification Sequence labeling Machine translation	Miyato et al. (2017), Ebrahimi et al. (2018b) Ebrahimi et al. (2018a), Cheng et al. (2019), Chen et al. (2020d)
Black-box attack	Token or Sentence	Medium	Text classification Sequence labeling Machine translation Textual entailment Dialogue generation Text Summarization	Jia and Liang (2017) Belinkov and Bisk (2017), Zhao et al. (2017) Ribeiro et al. (2018), McCoy et al. (2019) Min et al. (2020), Tan et al. (2020)
Hidden-space perturbation	Token or Sentence	High	Text classification Sequence labeling Speech recognition	Hsu et al. (2017), Hsu et al. (2018) Wu et al. (2019b), Chen et al. (2021) Malandrakis et al. (2019), Shen et al. (2020)
Interpolation	Token	High	Text classification Sequence labeling Machine translation	Miao et al. (2020), Chen et al. (2020c) Cheng et al. (2020b), Chen et al. (2020a) Guo et al. (2020)

Text data augmentation: Examples

- Lexical Substitution
  - Thesaurus-based substitution

[Courtesy: Amit Chaudhary https://amitness.com/2020/05/data-augmentation-for-nlp/]

Text data augmentation: Examples

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  - Thesaurus-based substitution
  - Word-embedding substitution

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Text data augmentation: Examples

- Lexical Substitution
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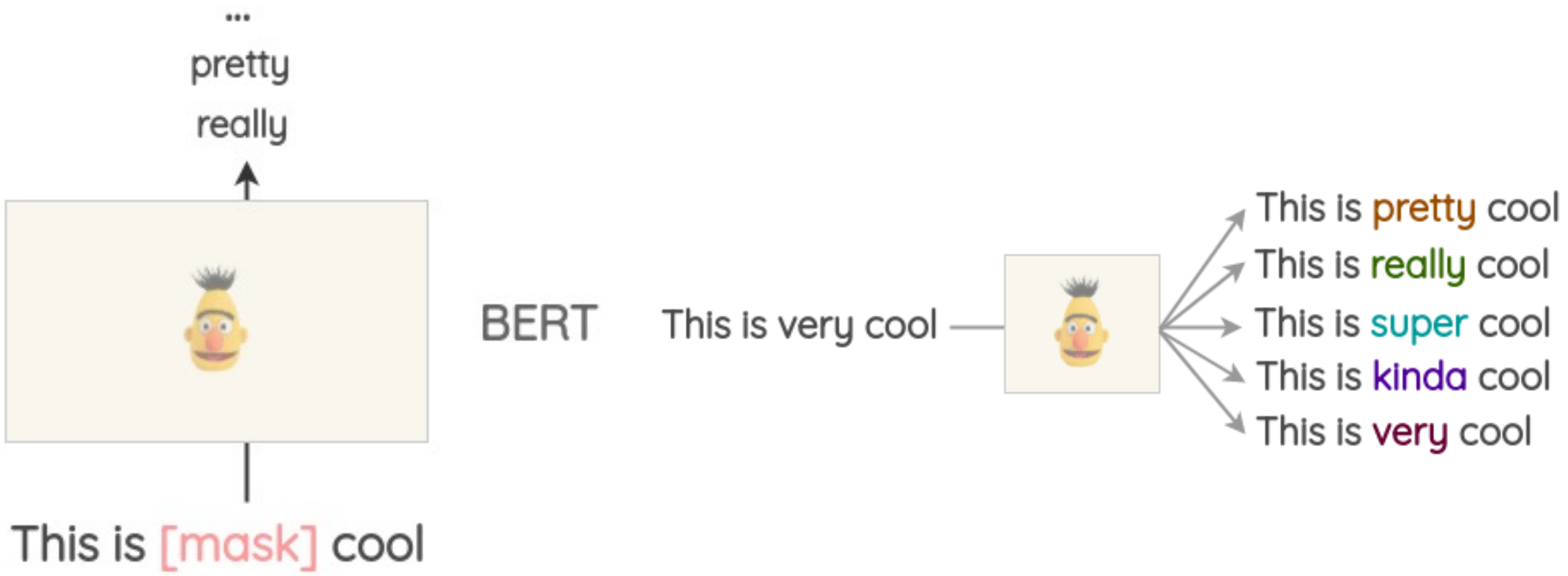
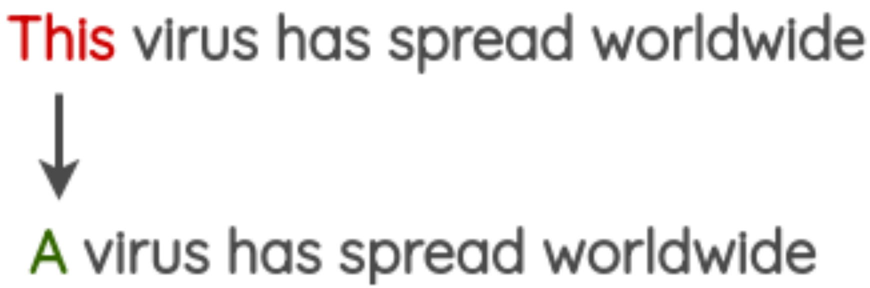
  - Word-embedding substitution
  - Masked LM



[Courtesy: Amit Chaudhary https://amitness.com/2020/05/data-augmentation-for-nlp/]

Text data augmentation: Examples

- Lexical Substitution
  - Thesaurus-based substitution
  - Word-embedding substitution
  - Masked LM
  - TF-IDF based word replacement
    - words that have low TF-IDF scores are uninformative and thus can be replaced without affecting the ground-truth labels of the sentence.



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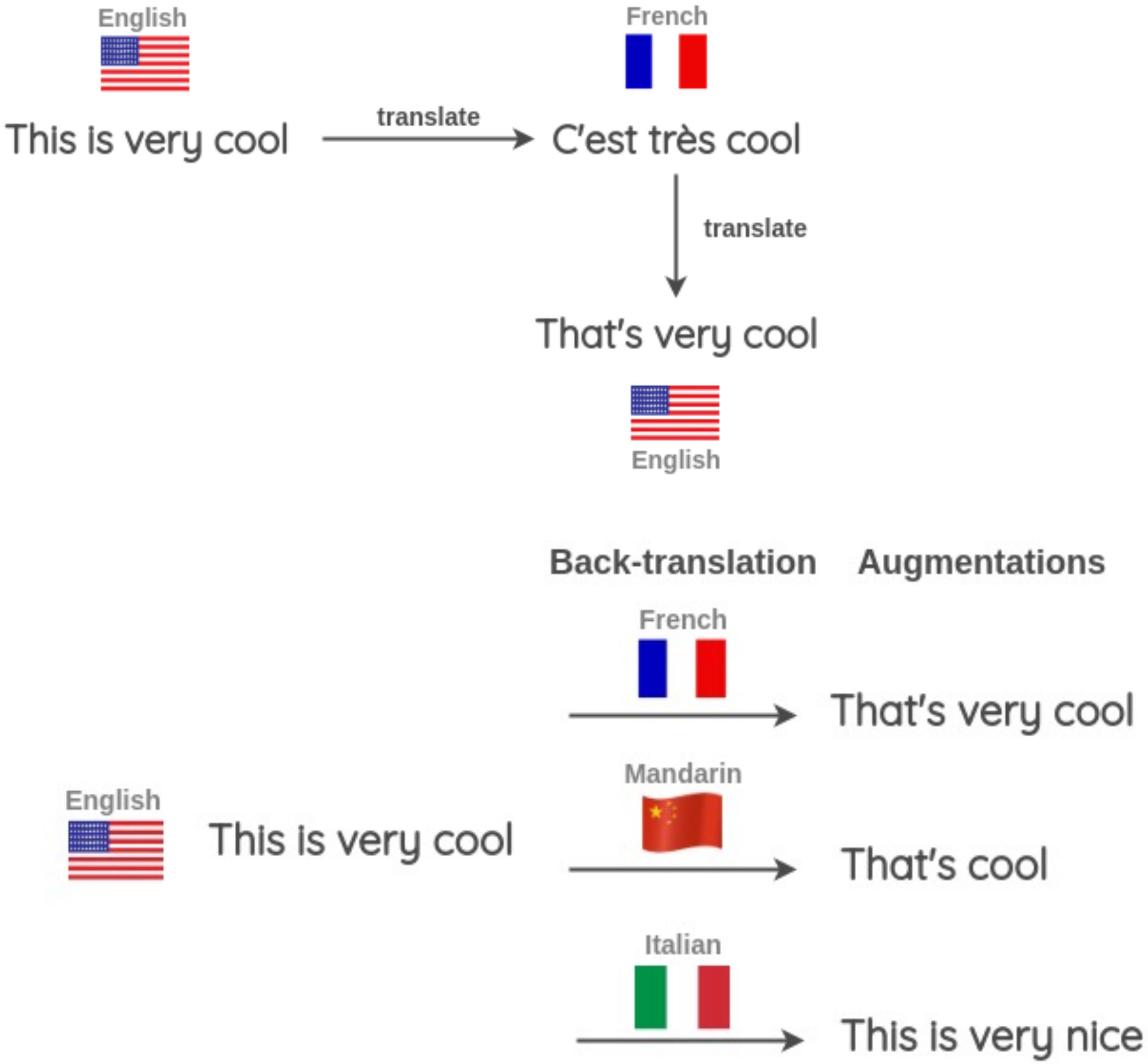
  - Back Translation



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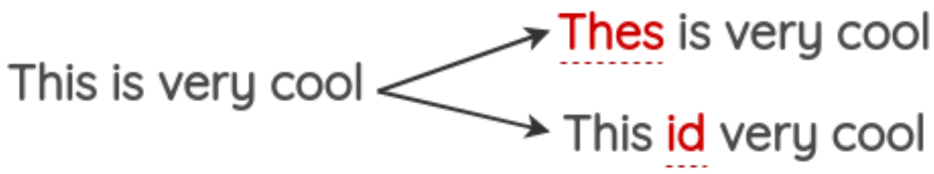
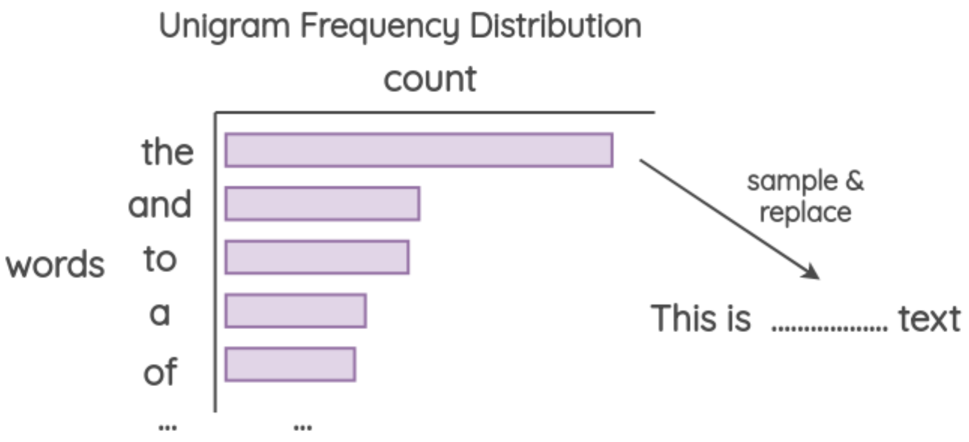
- Random Noise Injection

Spelling error:



Unigram noising:



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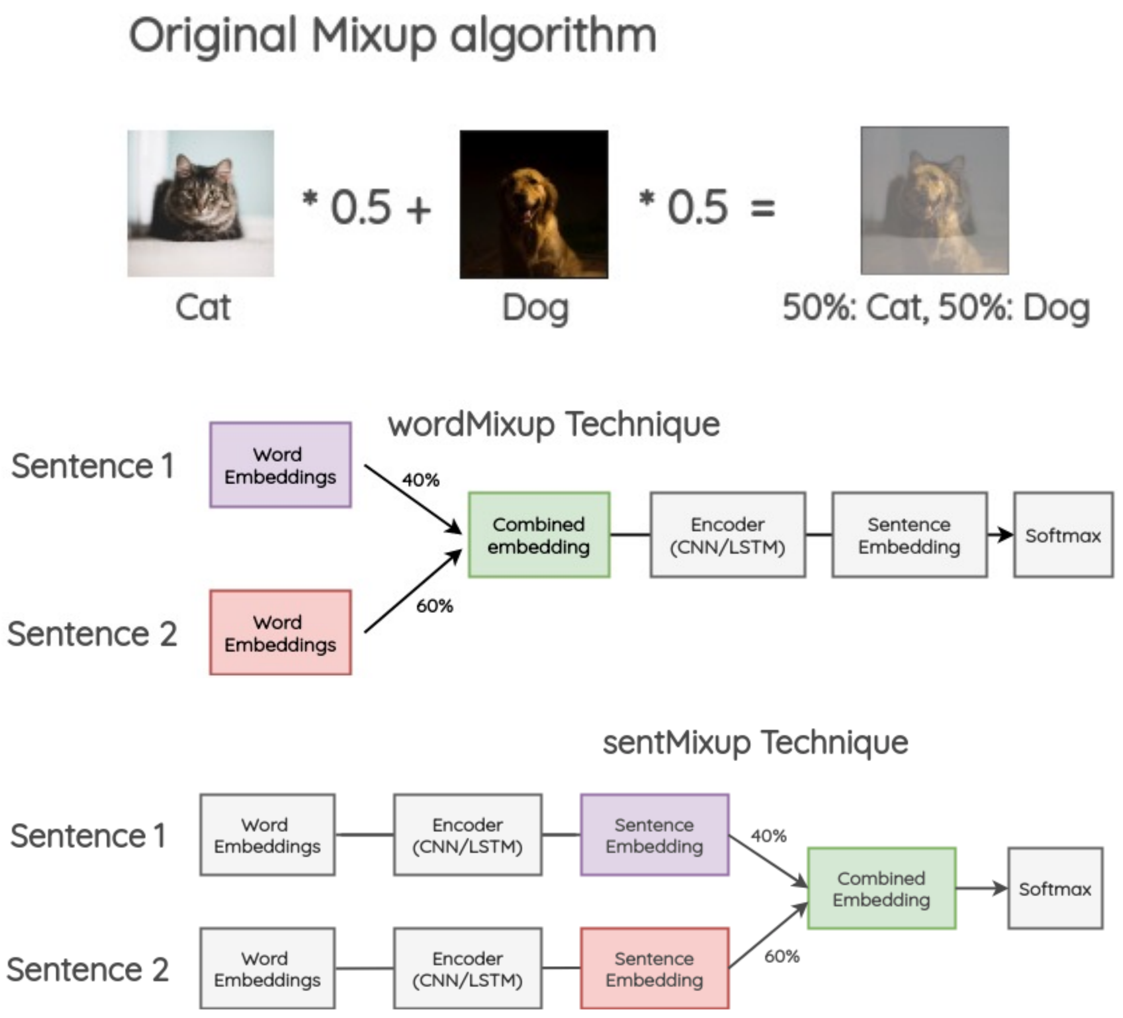
- MixUp



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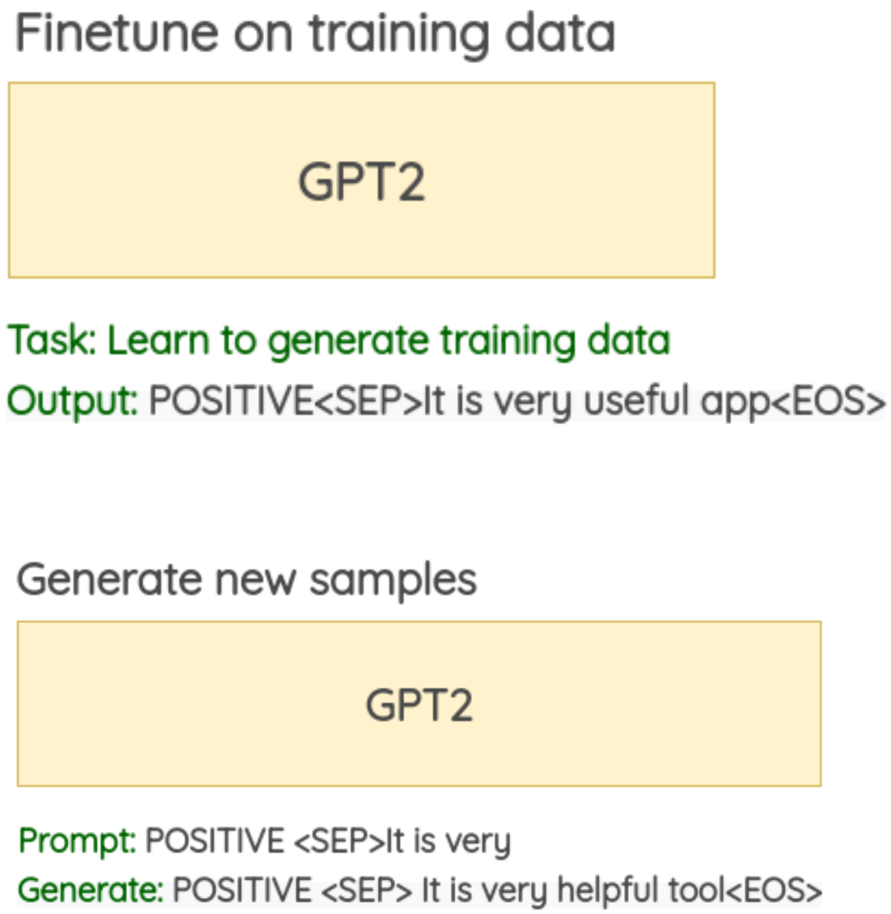
- Paraphrasing
  - Back Translation
- Random Noise Injection
- MixUp
- Generative Models
  - Finetune a large pre-trained LM (BERT, GPT2, etc)
  - Use the fine-tuned LM to generate new data



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Weakly Supervised Learning

The difficulty with supervised learning

- Annotated data is expensive and costs increase when...
  - *A task requires specialized expertise*

    E.g. "Only a trained linguist or a board certified radiologist can label my data"
  - *Labeling examples involves making multiple decisions*

    E.g. "Annotate this sentence with a parse tree"

    (instead of a single binary decision)

Credit: https://svivek.com/teaching/lectures/slides/weak-supervision/weak-supervision.pdf

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

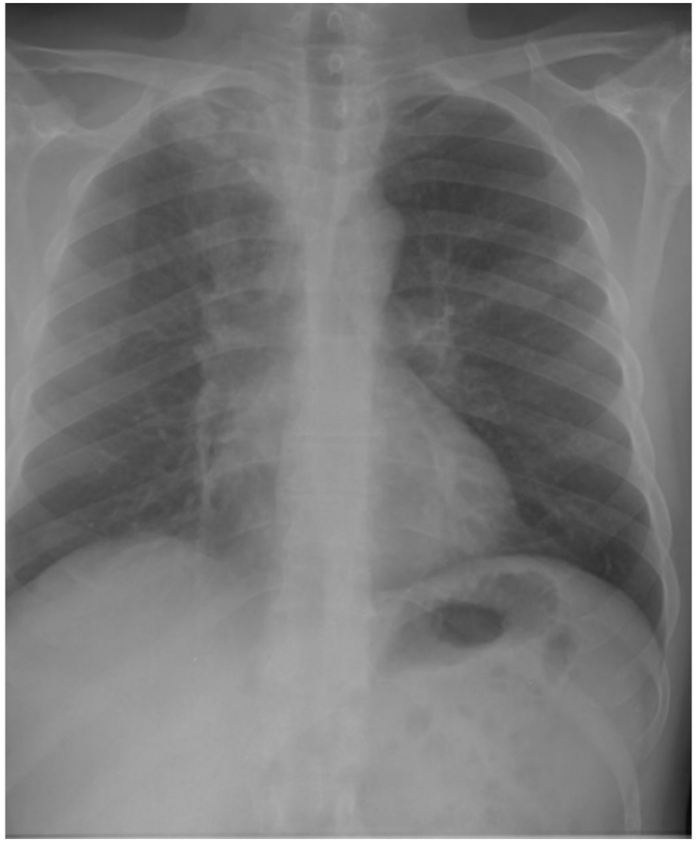
Use one or more (noisy / biased) pre-trained models to provide supervision

Transfer Learning: Use models already trained on a different task

Credit: https://dawn.cs.stanford.edu/2017/07/16/weak-supervision/

Example (I): labeling with heuristics

Task: Build a chest x-ray classifier
(normal/abnormal)

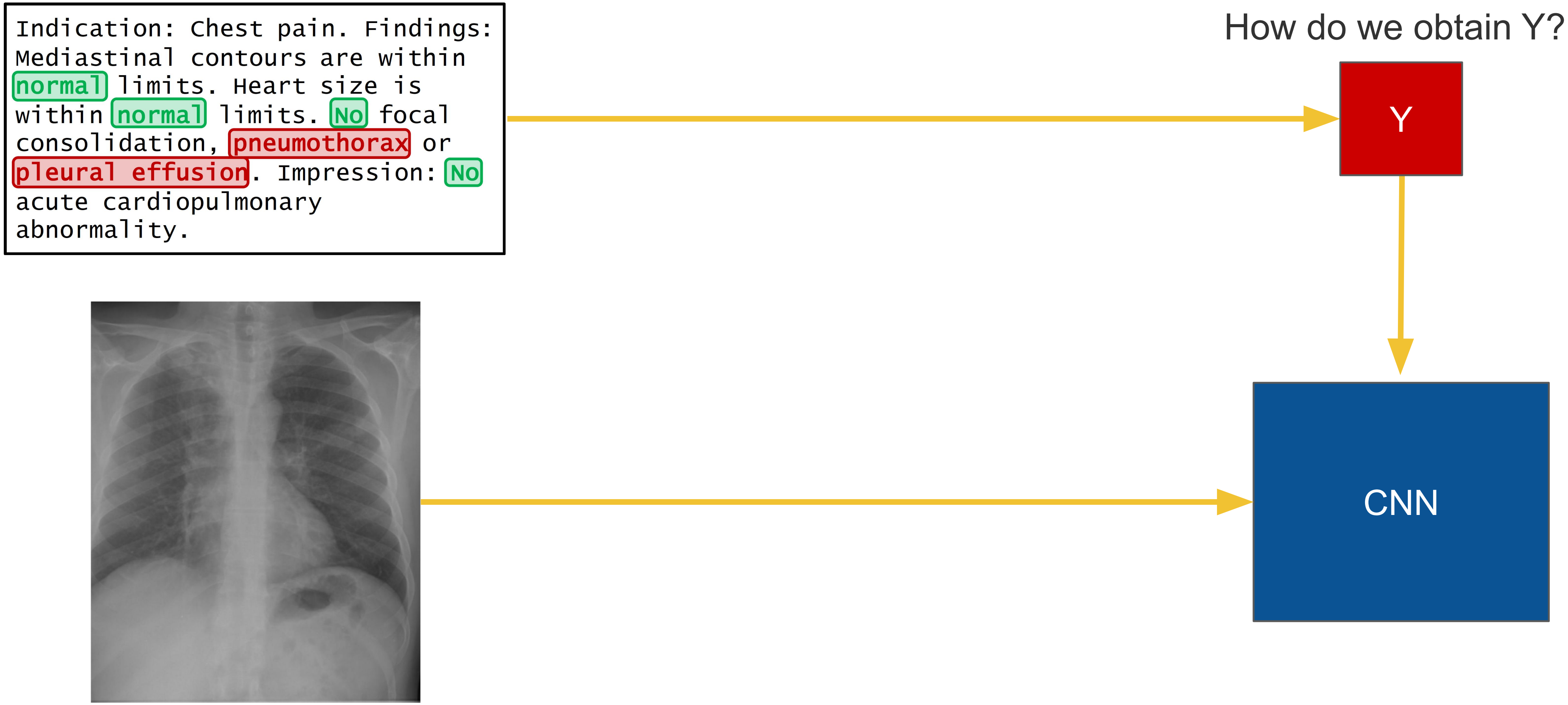


```
Indication: Chest pain. Findings:
Mediastinal contours are within
normal limits. Heart size is
within normal limits. No focal
consolidation, pneumothorax or
pleural effusion. Impression: No
acute cardiopulmonary
abnormality.
```

Can you use the accompanying medical report (text modality) to label the x-ray (image modality)?

[Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_ds07.pdf]

Example (I): labeling with heuristics



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Example (I): labeling with heuristics

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Normal Report

```
def LF_pneumothorax(c):
  if re.search(r'pneumo.*', c.report.text):
      return "ABNORMAL"

def LF_pleural_effusion(c):
  if "pleural effusion" in c.report.text:
      return "ABNORMAL"

def LF_normal_report(c, thresh=2):
    if len(NORMAL_TERMS.intersection(c.
     report.words)) > thresh:
      return "NORMAL"
```

LFs
(labeling functions)

Source: Khandwala et. al 2017, Cross Modal Data Programming for Medical Images

[Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_ds07.pdf]

Example (II): Labeling with knowledge bases

Task: relation extraction from text

- Hypothesis: If two entities belong to a certain relation, any sentence containing those two entities is likely to express that relation
- Key idea: use a *knowledge base* of relations to get lots of *noisy* training examples

Adapted from https://courses.cs.washington.edu/courses/cse517/13wi/slides/cse517wi13-RelationExtractionII.pdf

Example (II): Labeling with knowledge bases

Frequent Freebase relations

Relation name	Size	Example
/people/person/nationality	281,107	John Dugard, South Africa
/location/location/contains	253,223	Belgium, Nijlen
/people/person/profession	208,888	Dusa McDuff, Mathematician
/people/person/place_of_birth	105,799	Edwin Hubble, Marshfield
/dining/restaurant/cuisine	86,213	MacAyo's Mexican Kitchen, Mexican
/business/business_chain/location	66,529	Apple Inc., Apple Inc., South Park, NC
/biology/organism_classification_rank	42,806	Scorpaeniformes, Order
/film/film/genre	40,658	Where the Sidewalk Ends, Film noir
/film/film/language	31,103	Enter the Phoenix, Cantonese
/biology/organism_higher_classification	30,052	Calopteryx, Calopterygidae
/film/film/country	27,217	Turtle Diary, United States
/film/writer/film	23,856	Irving Shulman, Rebel Without a Cause
/film/director/film	23,539	Michael Mann, Collateral
/film/producer/film	22,079	Diane Eskenazi, Aladdin
/people/deceased_person/place_of_death	18,814	John W. Kern, Asheville
/music/artist/origin	18,619	The Octopus Project, Austin
/people/person/religion	17,582	Joseph Chartrand, Catholicism
/book/author/works_written	17,278	Paul Auster, Travels in the Scriptorium
/soccer/football_position/players	17,244	Midfielder, Chen Tao
/people/deceased_person/cause_of_death	16,709	Richard Daintree, Tuberculosis
/book/book/genre	16,431	Pony Soldiers, Science fiction
/film/film/music	14,070	Stavisky, Stephen Sondheim
/business/company/industry	13,805	ATS Medical, Health care

Adapted from https://courses.cs.washington.edu/courses/cse517/13wi/slides/cse517wi13-RelationExtractionII.pdf

Example (II): Labeling with knowledge bases

Corpus text

Bill Gates founded Microsoft in 1975.
Bill Gates, founder of Microsoft, …
Bill Gates attended Harvard from…
Google was founded by Larry Page …

Training data

Freebase

Founder: (Bill Gates, Microsoft)
Founder: (Larry Page, Google)
CollegeAttended: (Bill Gates, Harvard)

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Feature: X, founder of Y

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Label: Founder
Feature: X founded Y
Feature: X, founder of Y

(Bill Gates, Harvard)
Label: CollegeAttended
Feature: X attended Y

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Label: CollegeAttended
Feature: X attended Y

(Larry Page, Google)
Label: Founder
Feature: Y was founded by X

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Example (II): Labeling with knowledge bases

Negative training data

Can’t train a classifier with only positive data!
Need negative training data too!

Solution?
Sample 1% of unrelated pairs of entities.

Corpus text

Larry Page took a swipe at Microsoft...
...after Harvard invited Larry Page to...
Google is Bill Gates' worst fear ...

Training data

(Larry Page, Microsoft)
Label: NO_RELATION
Feature: X took a swipe at Y

(Larry Page, Harvard)
Label: NO_RELATION
Feature: Y invited X

(Bill Gates, Google)
Label: NO_RELATION
Feature: Y is X's worst fear

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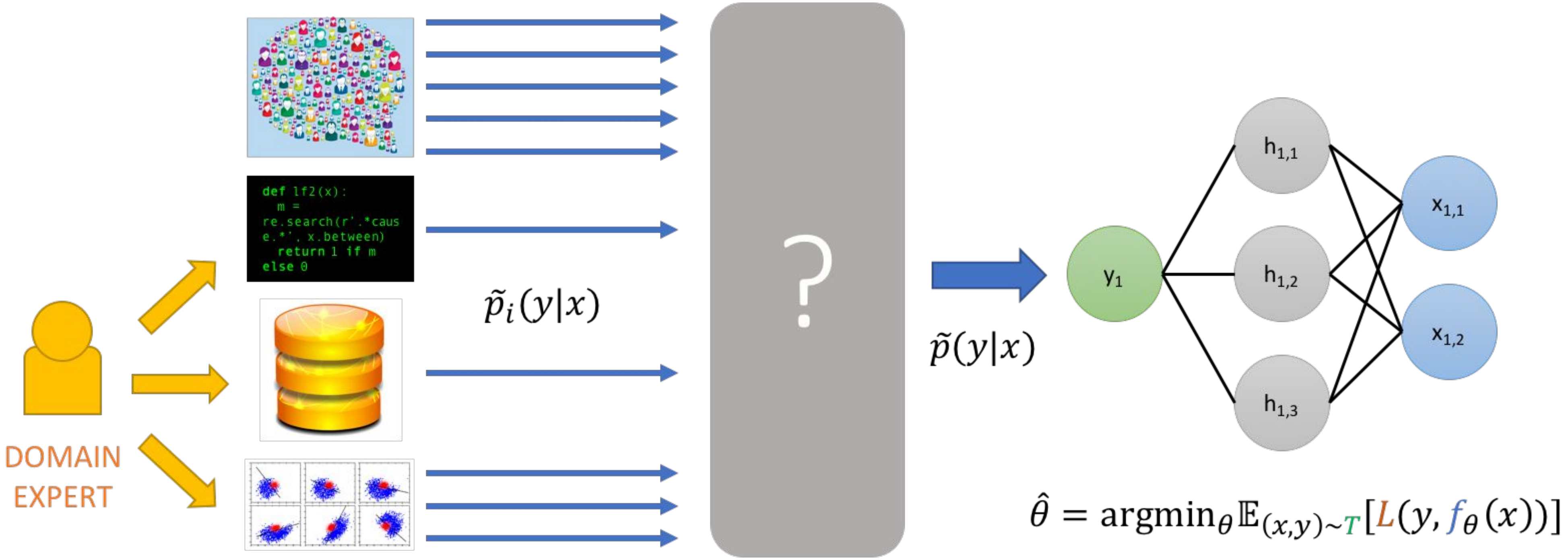
Integrating multiple noisy labels



Example Weak Supervision Sources

Technical Challenge: Integrating & Modeling Diverse Sources

Use Weak Supervision to Train End Model

Source: A. Ratner et. al https://dawn.cs.stanford.edu/2017/07/16/weak-supervision/

[Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_ds07.pdf]

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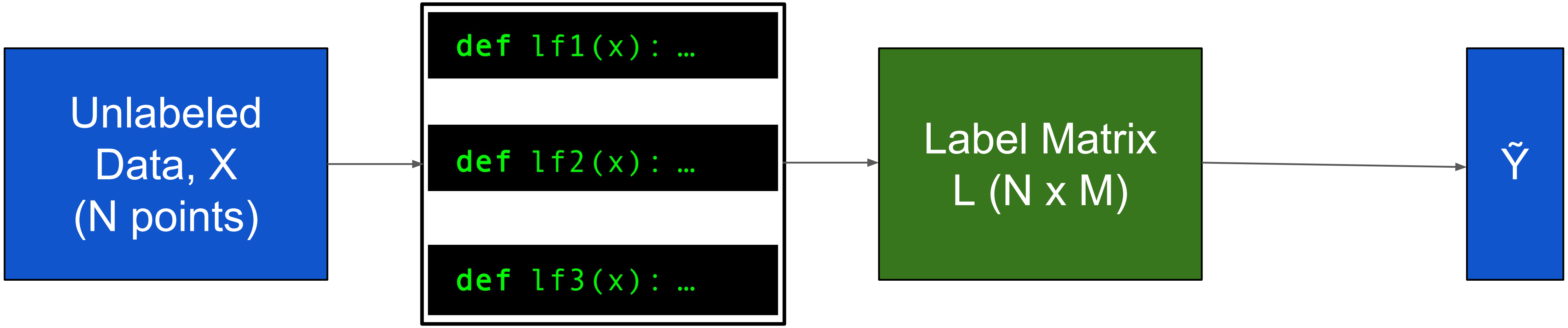

Labeling functions
(M functions)

[Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_ds07.pdf]

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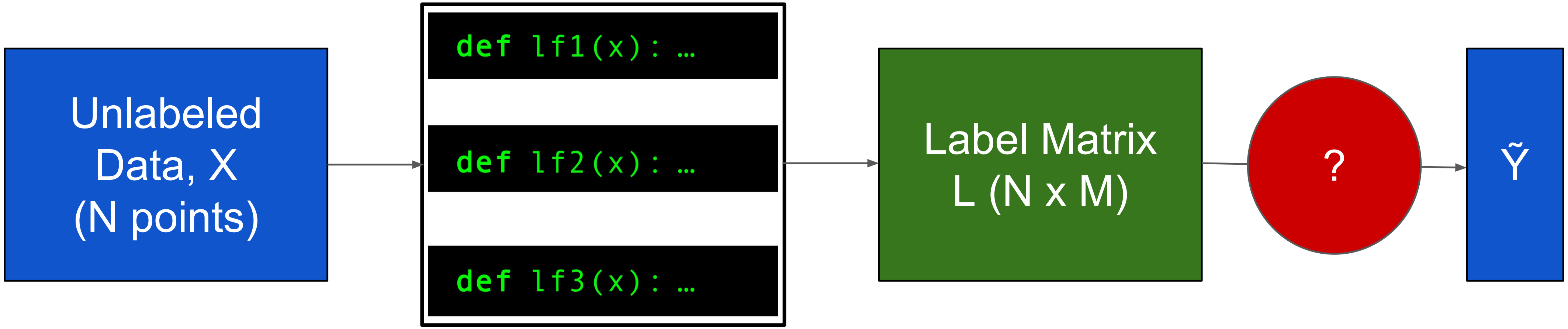

Labeling functions
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Integrating multiple noisy labels

How do we obtain probabilistic labels, $\tilde{\mathbf{Y}}$, from the label matrix, **L**?

Approach 1 - Majority Vote

Take the majority vote of the labelling functions (LFs).

Let's say **L** = [[0, 1, 0, 1, 0]; [1, 1, 1, 1, 0]].

$\tilde{\mathbf{Y}}$ = [0, 1]

[Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_ds07.pdf]

Integrating multiple noisy labels

How do we obtain probabilistic labels, $\tilde{\mathbf{Y}}$, from the label matrix, **L**?

Approach 1 - Majority Vote

Majority vote fails:

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LFs

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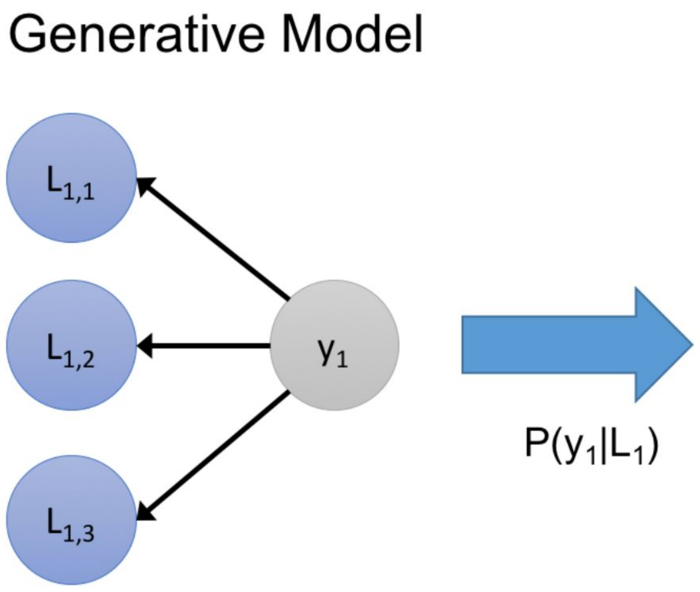
Integrating multiple noisy labels

How do we obtain probabilistic labels, $\tilde{\mathbf{Y}}$, from the label matrix, $\mathbf{L}$?

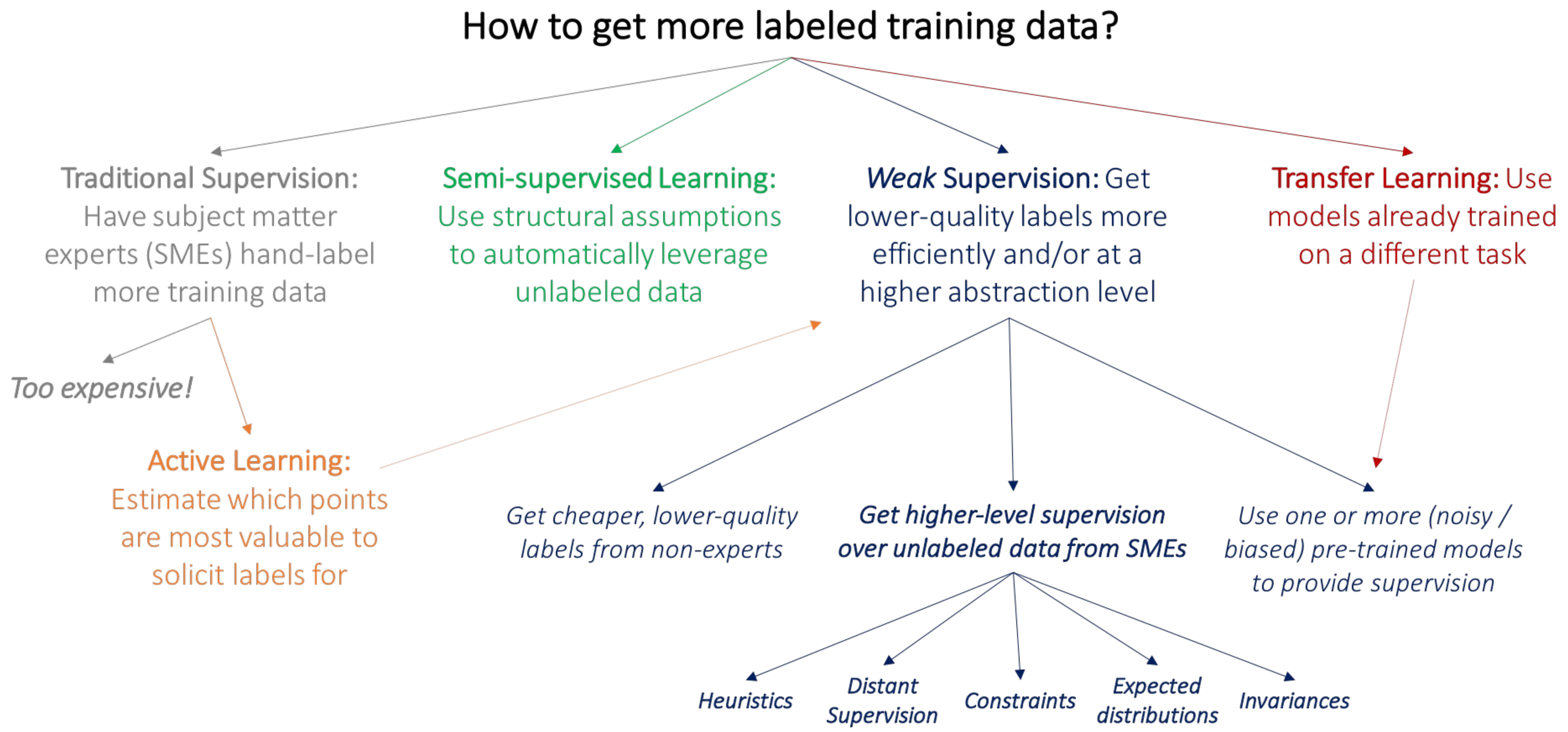
Approach 2

Train a generative model over **P(L, Y)** where **Y** are the **(unknown)** true labels



[Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_ds07.pdf]

Summary: Weak/distant supervision



Summary: Weak/distant supervision

- Noisy labels from heuristics, knowledge bases, constraints, …
- Integrating multiple noisy labels
  - Majority vote
  - Generative modeling
  - …

- Not all information/experiences can easily be converted into labels
  - "Every part of speech sequence should have a verb"
  - "In a sentence with word 'but', the sentiment of text after 'but' dominates"
  - "Every image patch that is recognized as a bicycle should have at least one patch that is recognized as a wheel"
  - I have a "discriminator" model that can tell me whether a model-generated image is good or not
- Need a more flexible framework to incorporate all forms of experiences

Questions?