

Learning with Weak Supervision

(弱监督机器学习范式)

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Big Data

Essential Goal

Turn data into information and knowledge, so as to support sound decision making

Key Techniques

Cloud Computing



Managing Data

Crowdsourcing



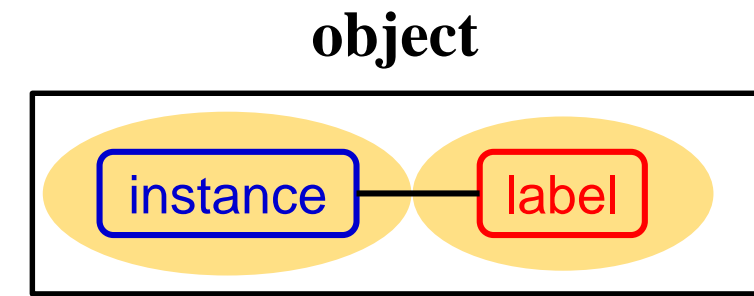
Collecting Data

Machine Learning



Analyzing Data

Traditional Supervised Learning

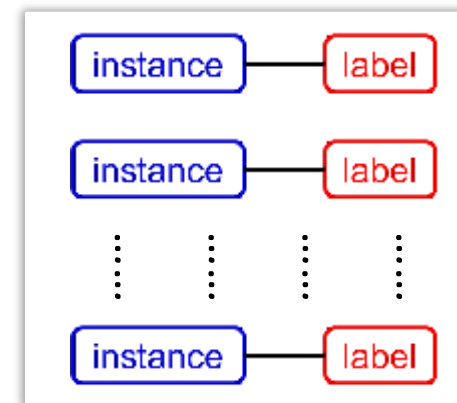
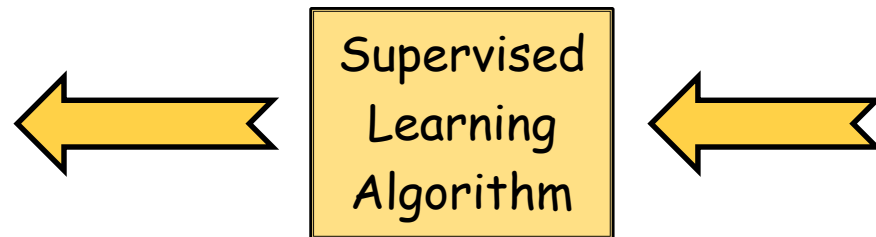
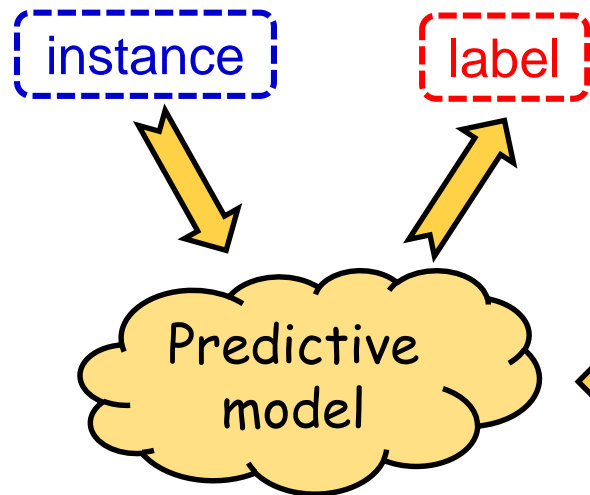


Input Space

represented by a **single instance** (feature vector) characterizing its properties

Output Space

associated with a **single label** characterizing its semantics



Basic Assumption: Strong Supervision



Key factor for successful learning

(encoding *semantics* and *regularities* for the learning problem)

Strong supervision assumption

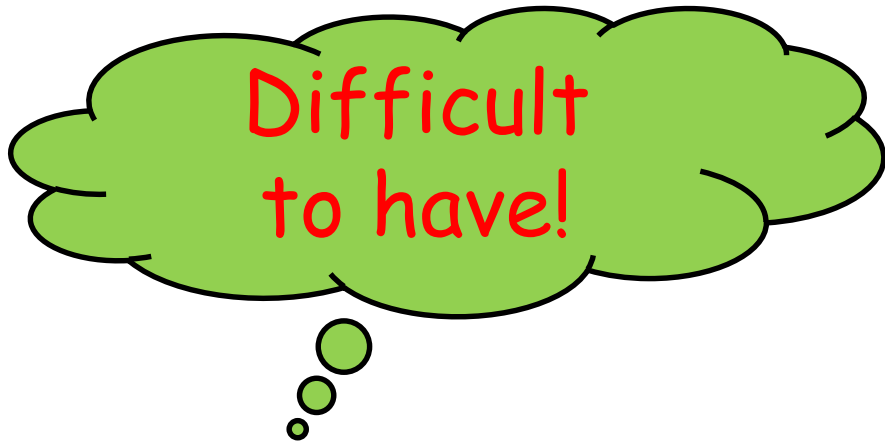
- Sufficient labeling

abundant labeled training data are available

- Explicit labeling

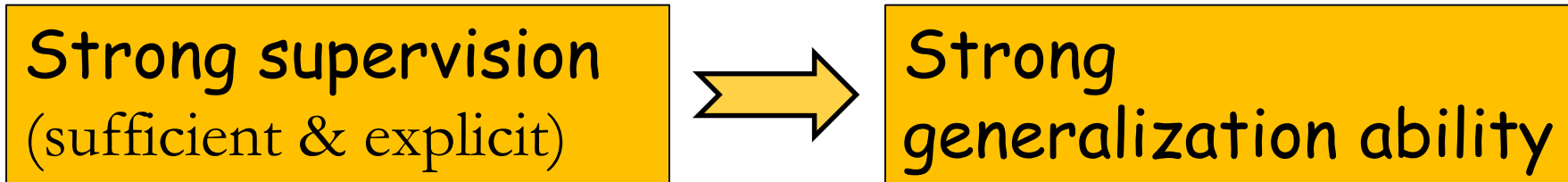
object labeling is unique and unambiguous

But, Supervision Is Usually Weak



Constrained by:

- ❑ Limited resources
- ❑ Physical environment
- ❑ Problem properties
- ❑



In practice, we usually have to learn with weak supervision

Learning with Weak Supervision

- ✓ **Insufficient labeling**

Labeled Data + Unlabeled Data

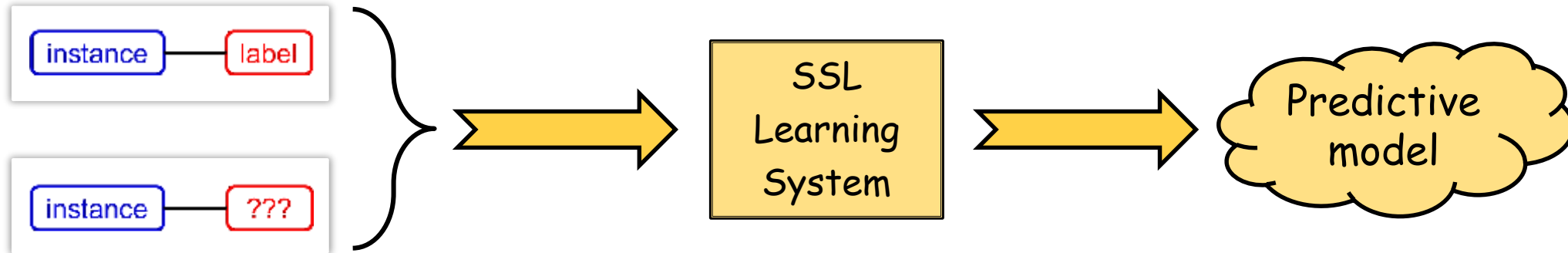
- ✓ **Non-Unique labeling**

Multi-Label Data (labeling with multiple valid labels)

- ✓ **Ambiguous labeling**

Partial-Label Data (labeling with multiple candidate labels)

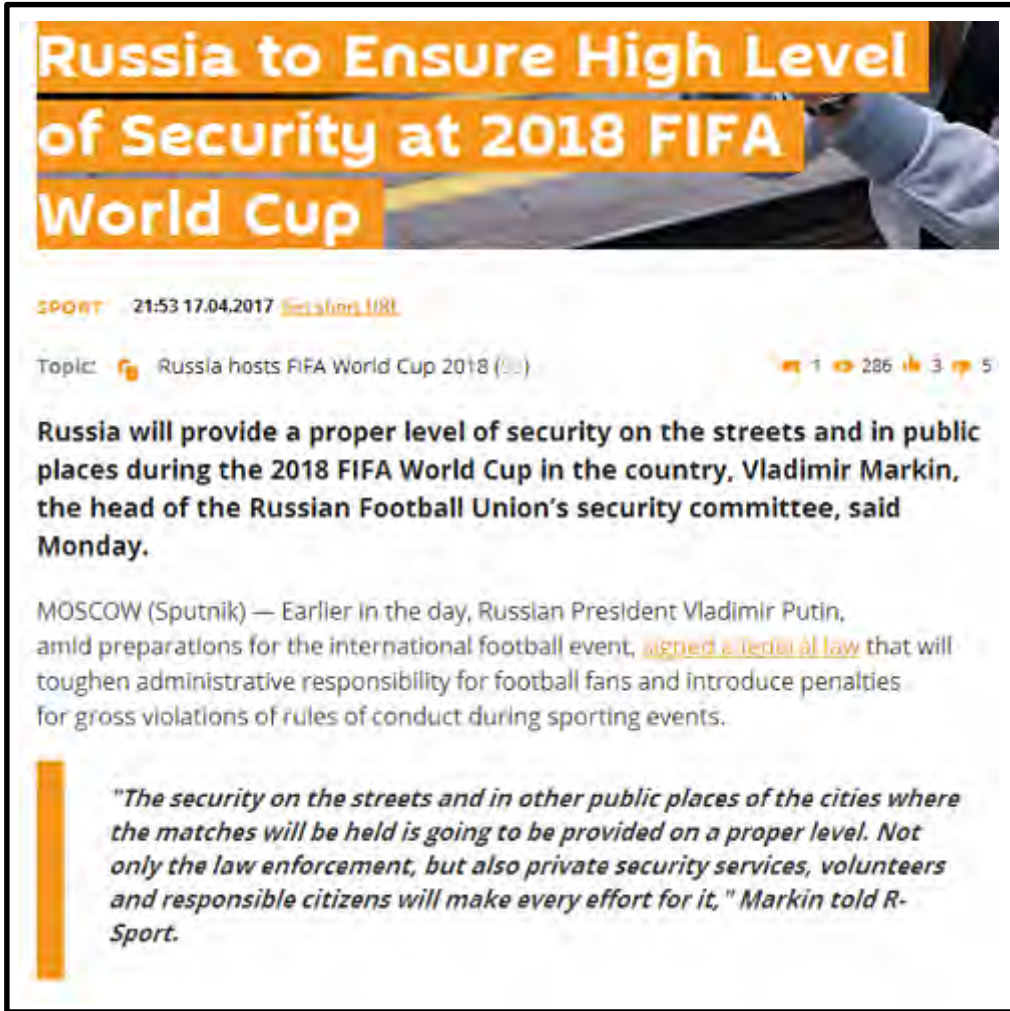
Semi-Supervised Learning (SSL)



Major paradigm in exploiting unlabeled data to improve generalization performance, without human interventions

- ❑ **Generative methods** [Miller & Uyar, NIPS'97] [Nigam et al., MLJ00]
- ❑ **S3VMs** [Joachims, ICML'99] [Chapelle & Zien, AISTATS'05] [Grandvalet & Bengio, NIPS'05]
- ❑ **Graph-based methods** [Zhu et al., ICML'03] [Zhou et al., NIPS'04] [Belkin et al., JMLR06]
- ❑ **Disagreement-based methods** [Blum & Mitchell, COLT'98] [Zhou & Li, KAIS10]

Multi-Label Objects

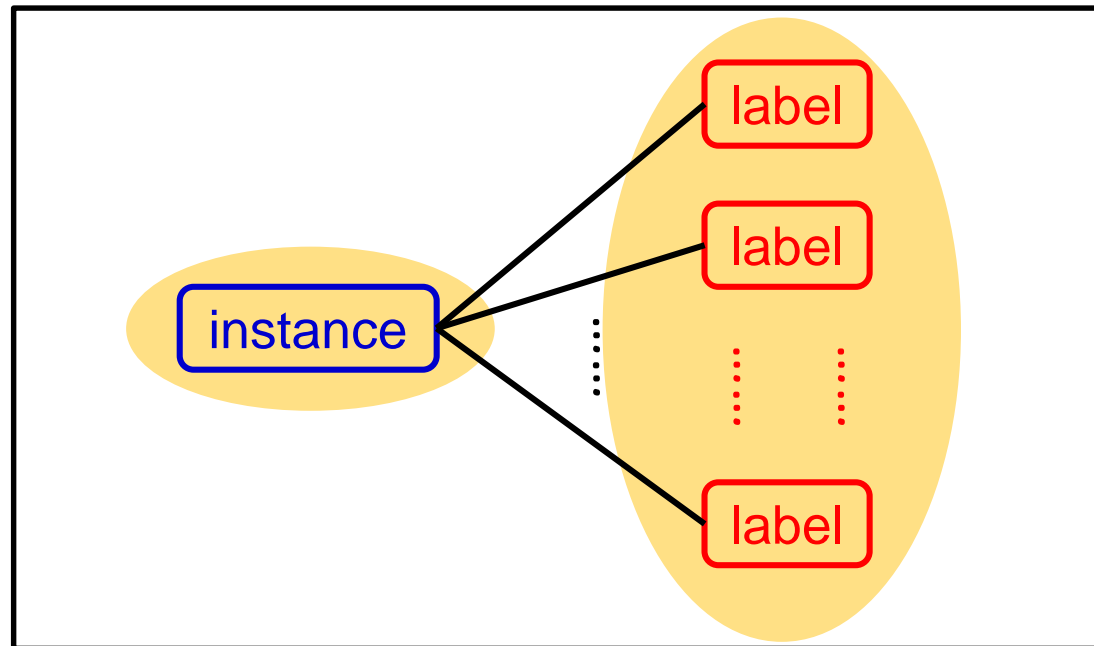


- Sports
- Europe
- Economics
- Travel
- Government
-

Multiple labels

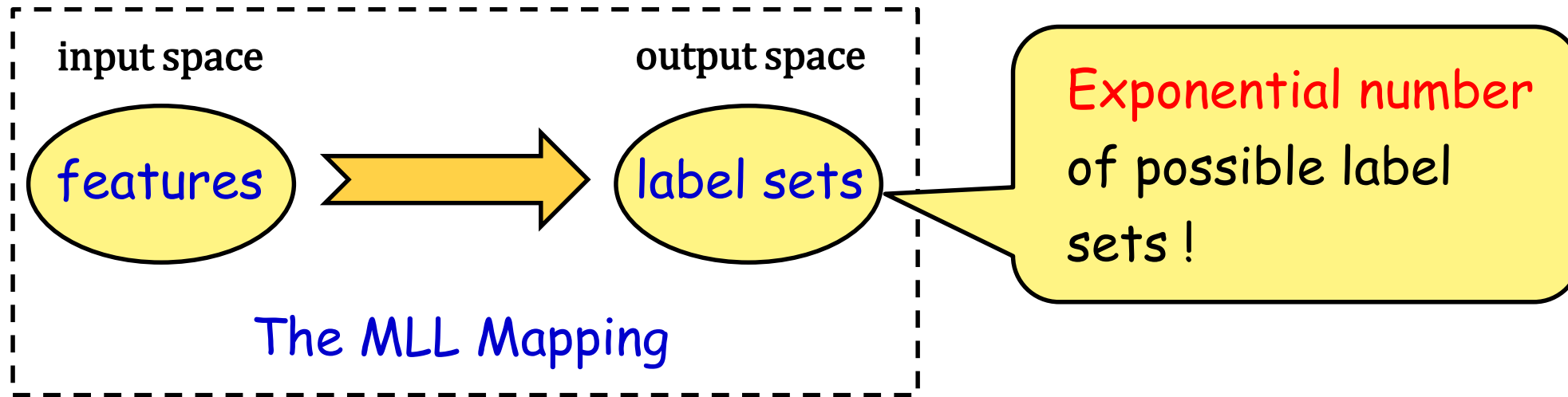
Multi-Label Learning (MLL)

object



Multi-Label Learning (MLL)

Major Challenge of MLL



$q=5 \rightarrow 32$ label sets

$q=10 \rightarrow \sim 1\text{k}$ label sets

$q=20 \rightarrow \sim 1\text{M}$ label sets

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Supervision Info.

□ Individually strong

□ But, globally weak !

Partial Label

Appreciator A ----->



-----> Picasso style ✗

Appreciator B ----->

-----> Monet style ✗

Appreciator C ----->

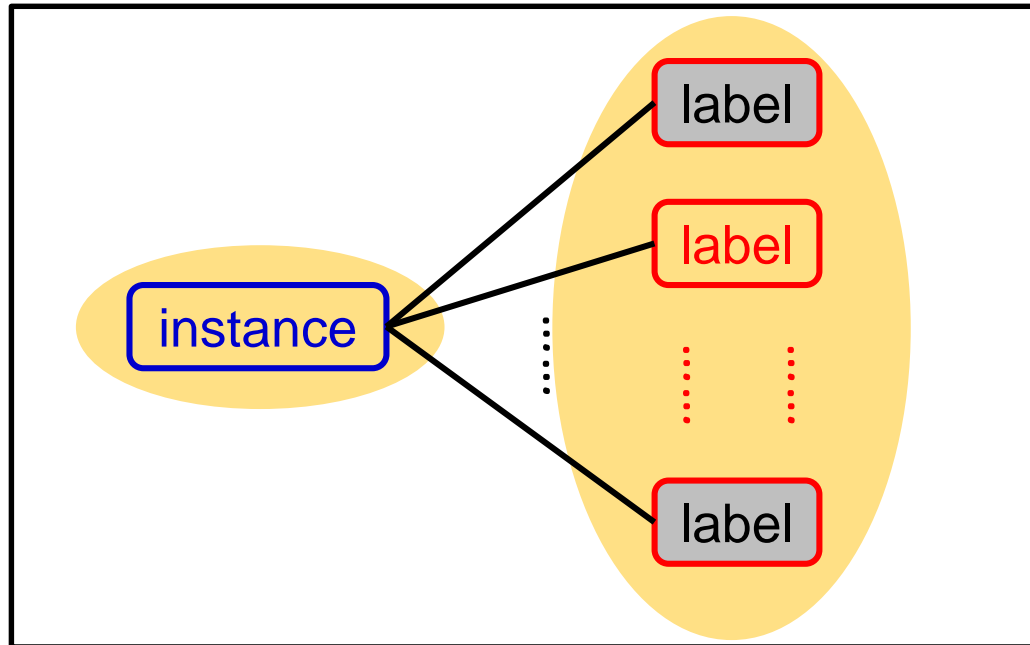
-----> van Gogh style ✓

Widely exist in real-world applications

- ❑ Computer vision [Cour et al., JMLR11] [Tang & Zhang, AAAI'17]
- ❑ Image classification [Zeng et al., CVPR'13] [Chen et al., CVPR'13]
- ❑ Learning from crowds [Raykar et al., JMLR10] [Yu & Zhang, MLJ17]
- ❑ Ecoinformatics [Liu & Dietterich, NIPS'12] [Zhang & Yu, IJCAI'15]
- ❑

Partial-Label Learning (PLL)

object



□ Each object is associated with **multiple candidate labels**

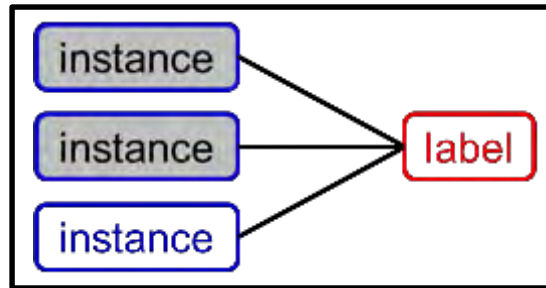
□ Only one of the candidate label is the **unknown ground-truth label**

Partial-Label Learning (PLL)

Other Scenarios Widely Exist

multi-instance learning

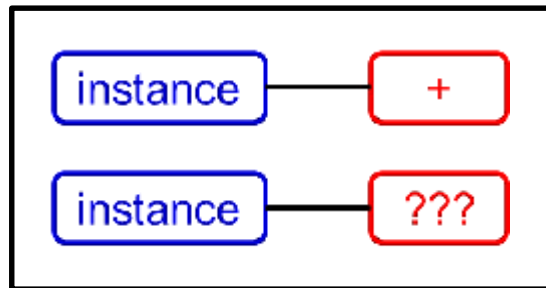
[Dietterich et al., AIJ97] [Foulds & Frank, KER10] [Amores, AIJ13]



ambiguous labeling

PU learning

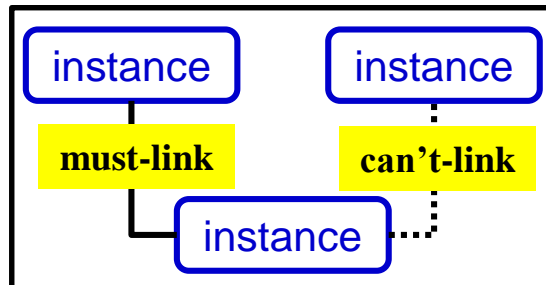
[Liu et al., ICML'02] [Liu et al., ICDM'03] [Li et al., ACL'10]



insufficient labeling

learning with constraints

[Wagstaff et al., ICML'01] [Basu et al., CRCBook08]



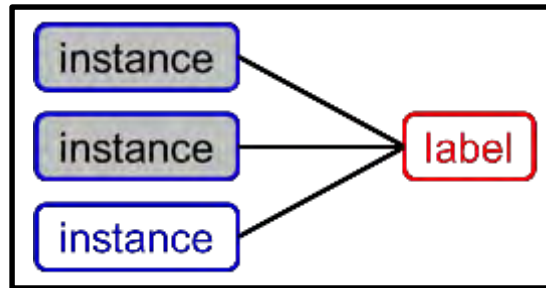
non-unique labeling

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Other Scenarios Widely Exist

multi-instance learning

[Dietterich et al., AIJ97] [Foulds & Frank, KER10] [Amores, AIJ13]



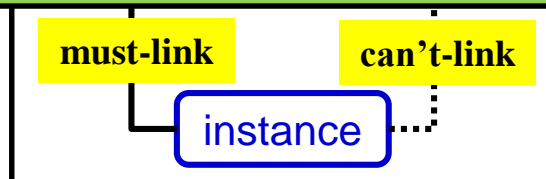
ambiguous labeling

Learning with Weak Supervision

Framework + Model + Utilization

lea

[Wagstaff et al., ICML'01] [Basu et al., CRCBook08]



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Thanks!

