Theoretical Analysis of Indirect Supervision

Indirectly Supervised Natural Language Processing (Part IV)

Qiang Ning
AWS AI Labs

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ACL Tutorials

Indirectly Supervised Natural Language Processing

What to expect

- We pose the challenge to define a principled way to measure the benefits of these signals to a given downstream task, and the challenge to further understand why and how these signals can help reduce the complexity of the learning problem in theory.
- Main papers

  [EMNLP’21] Foreseeing the Benefits of Incidental Supervision

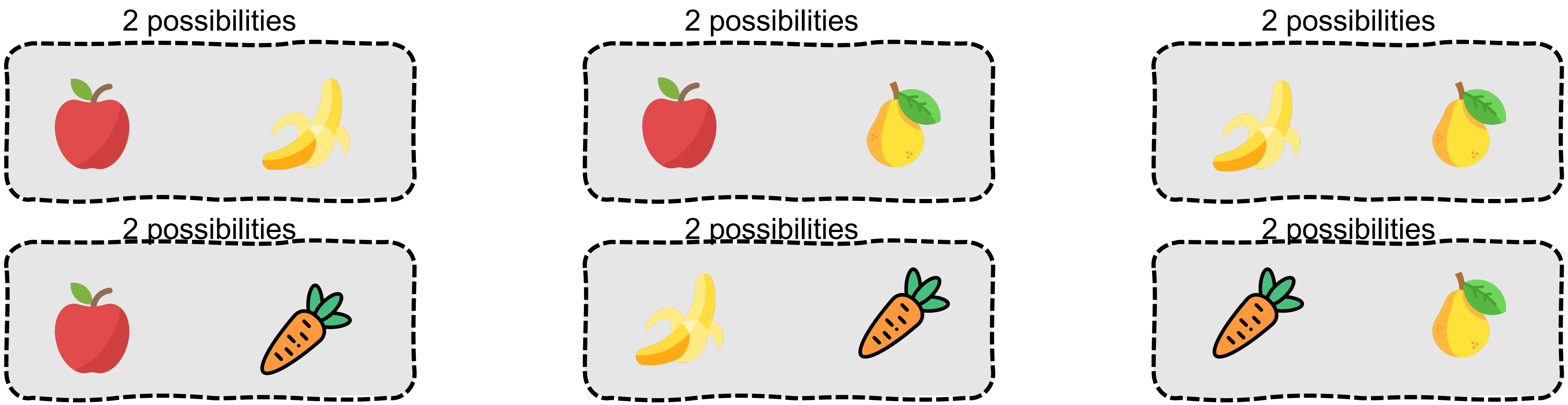
  [NeurIPS’20] Learnability with Indirect Supervision Signals

Let’s Walk Through A Toy Example

Task: Pair-wise Relationship Between Entities

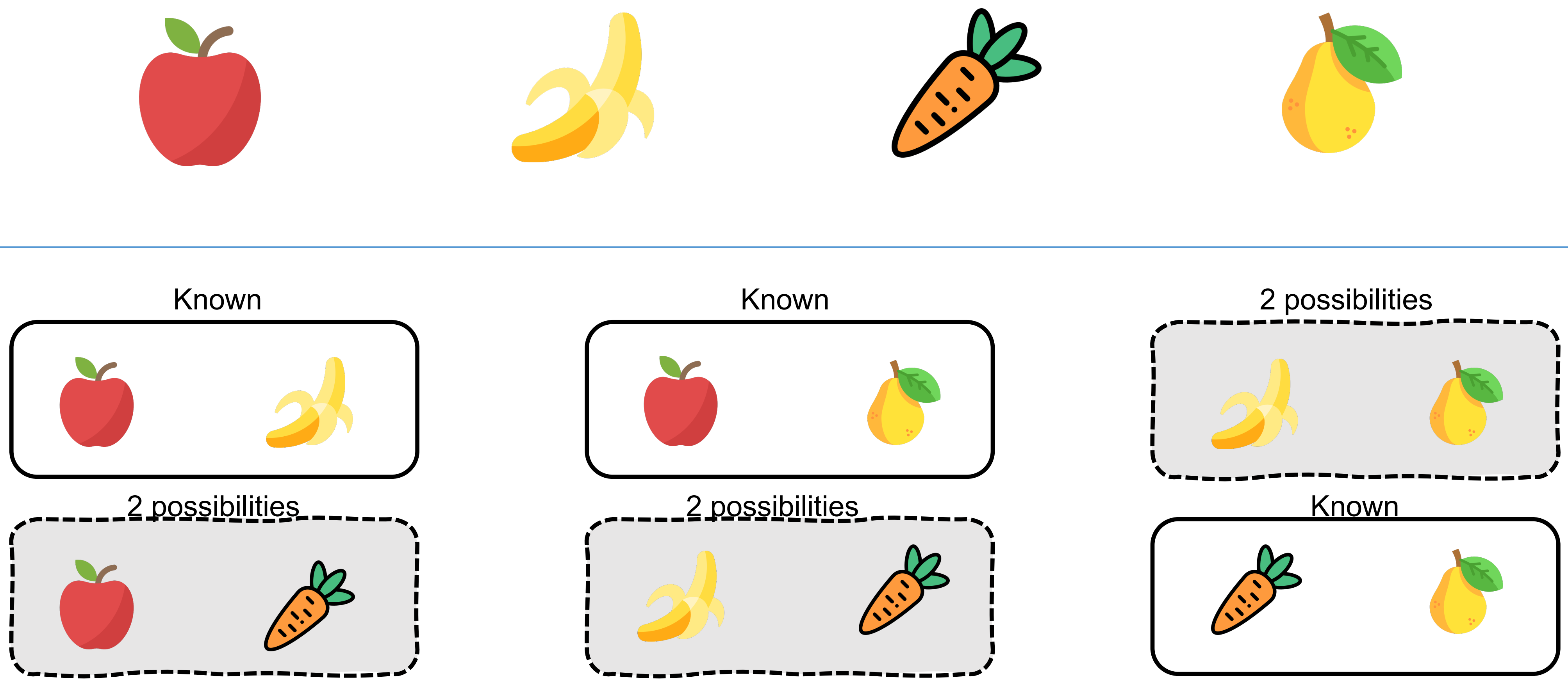
Thanks to Freepik and Flaticon for creating and sharing the icons freely.

Six Pairs of Relationships



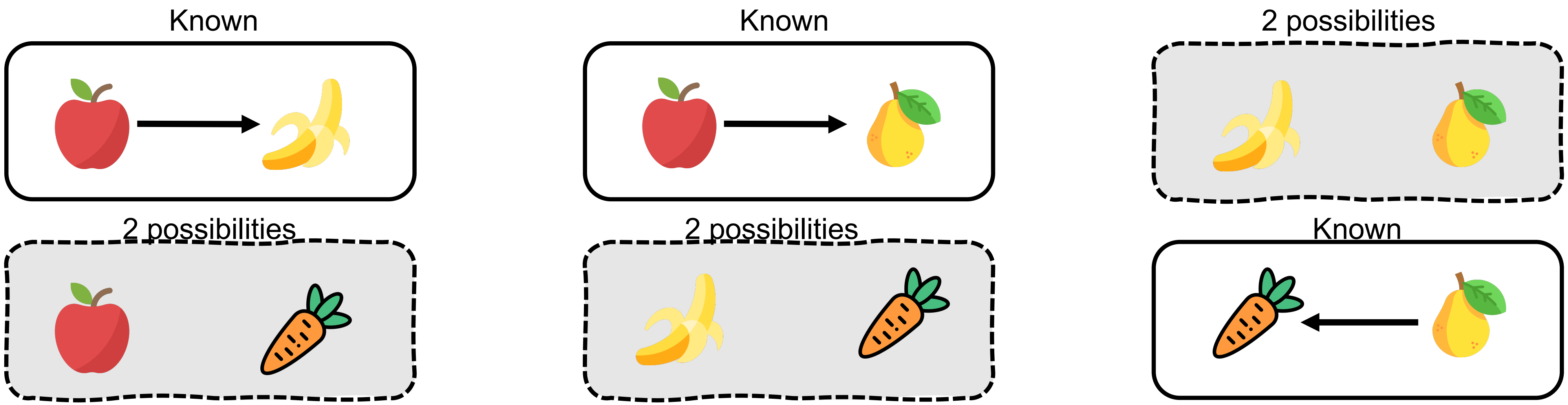
If each relation can choose from a label set of 2 labels, then there are 2^6 possibilities.

Six Pairs of Relationships



Suppose that we already know the label for 3 pairs of them. The total number of possibilities is reduced from $2^6=64$ to $2^3=8$. In other words, we still know nothing about the remaining 3 pairs of relationships.

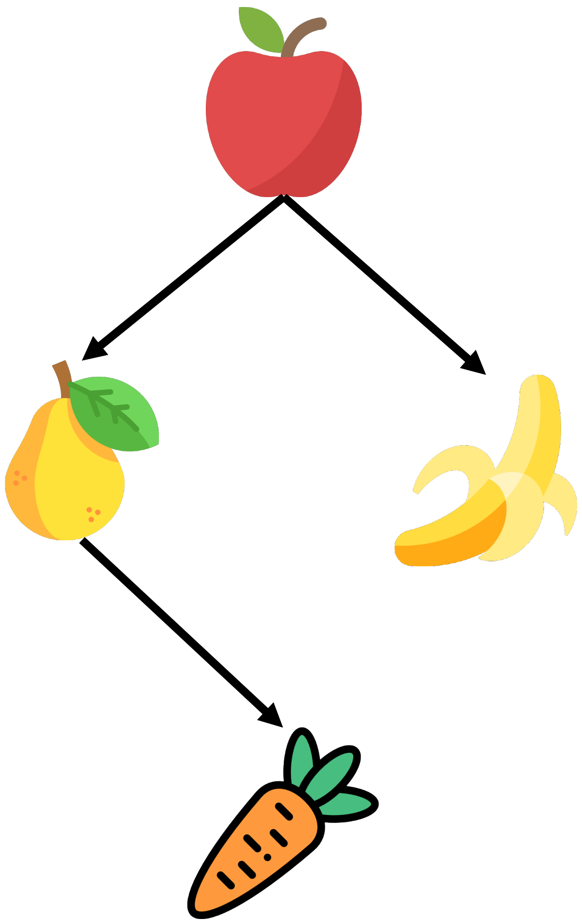
Introducing A Structure Among the Entities



Now, assume that we learn more information about the problem!
(1) the pair-wise relation between entities is an "order relation"
(2) all of the entities create a Directed Acyclic Graph (DAG)

Introducing A Structure Among the Entities

Now with 3 known edges, we have a “partial order.”



Introducing A Structure Among the Entities

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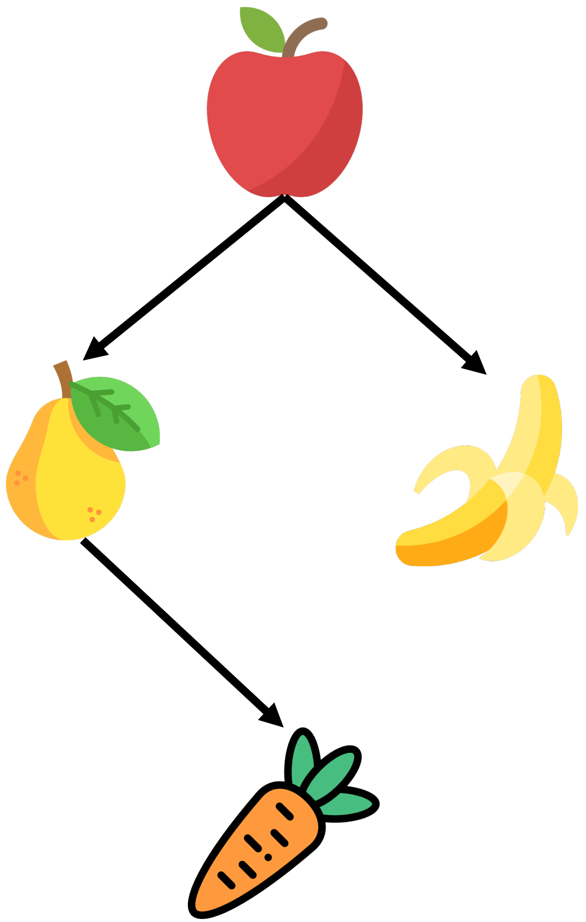
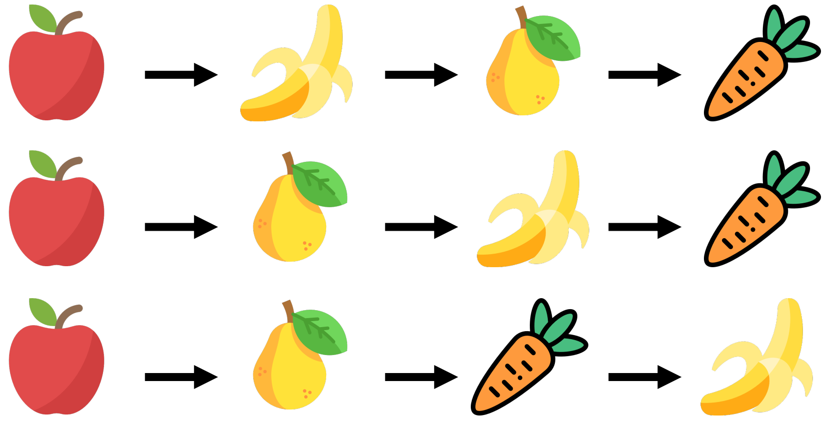
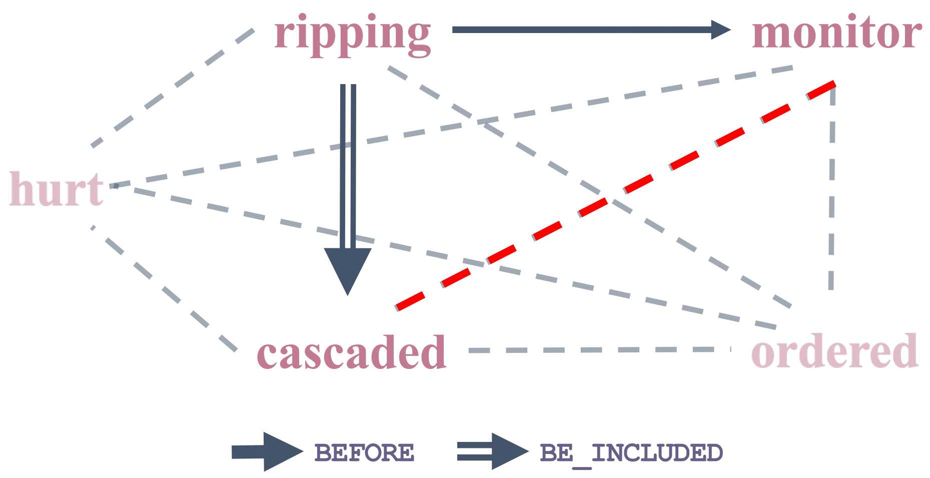


There are only 3 possibilities to describe the entities now (also known as the linear extensions of the partial order).



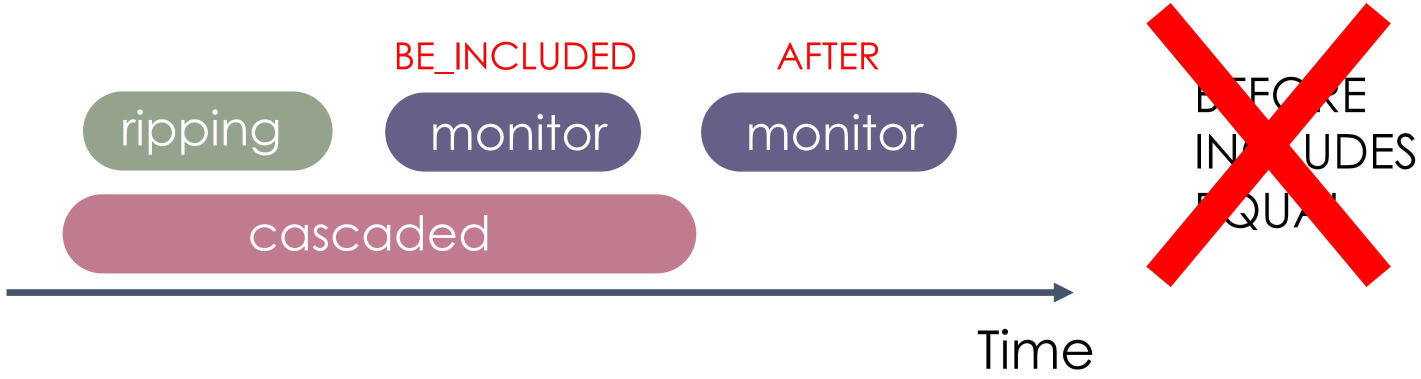
Remember the number of possibilities would have been 2^3=8 if we hadn't known this structure.

A Relevant Example in NLP is Temporal Relationship Classification



Temporal relation graph: Nodes are events and edges are temporal relationships. It is more complex than a DAG because the edges can choose from more than two directions (depending on the setup, there can be as many as 13[1] labels representing the temporal relationship between two events).

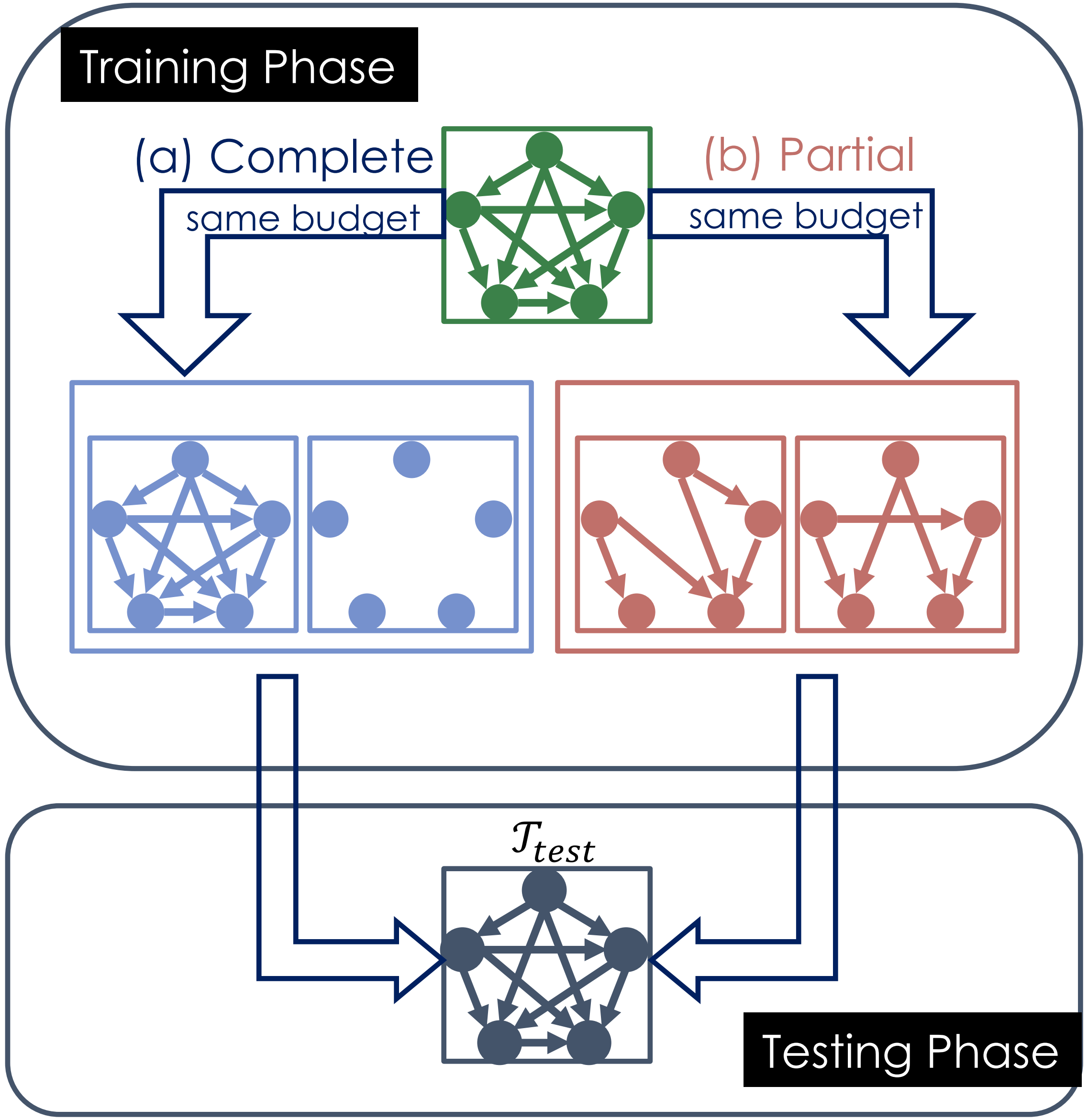
But the concept remains the same – the uncertainty is reduced because of the structure of the problem.



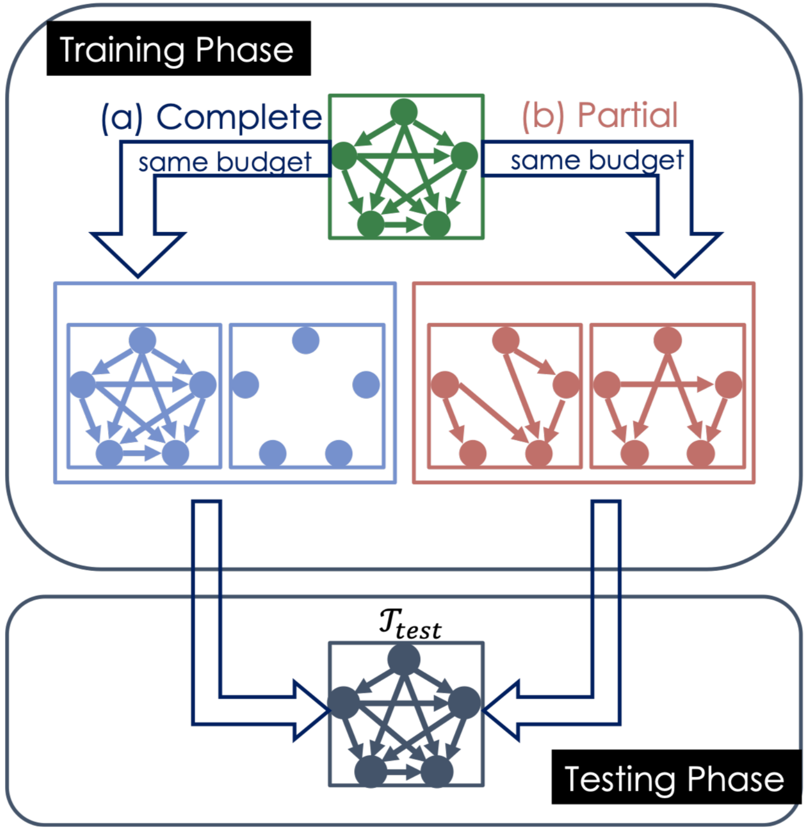
We "indirectly" learn something about the red edge from other edges.

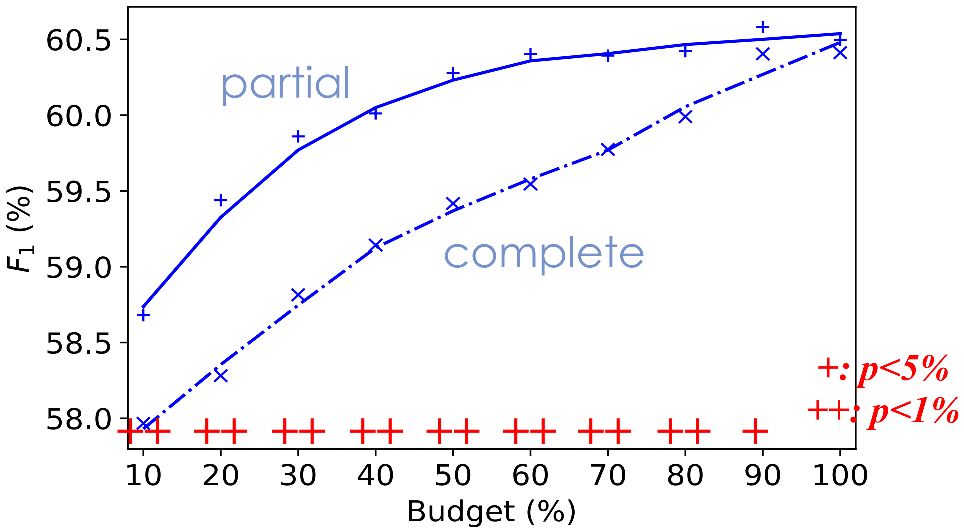
[1] Joint Reasoning for Temporal and Causal Relations. Ning et al., ACL'18.

Partial or complete, that's the question *[NAACL'19]*



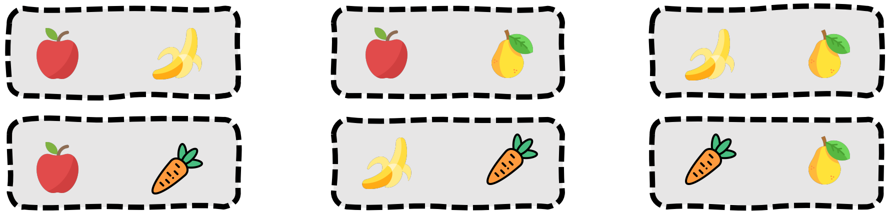
Partial or complete, that's the question *[NAACL'19]*





- *Even if some annotations are partial, we "indirectly" learn information about the unannotated edges, so when we have a fixed budget, we can gain more "information" and achieve higher performance.*
- *How do we **quantify** the information brought by the structure?*

Quantifying Information: Problem Setup



d=6 variables to be labeled

The relation network should be a DAG

Structure: a vector of random variables: $Y = [Y_1, Y_2, \dots, Y_d]$

Let $\mathcal{L}$ be the label set

$$Y \in C(\mathcal{L}^d) \subseteq \mathcal{L}^d$$

Not all assignments are valid
(aka "constraints")

Annotation:

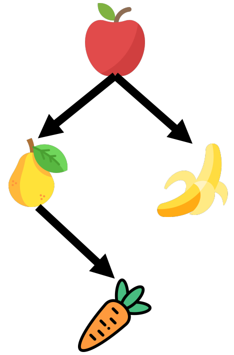
k out of d variables are labeled → Y is further limited to a subset of $C(\mathcal{L}^d)$

Let $\boldsymbol{f_k}$ **be the size of the feasible subset**

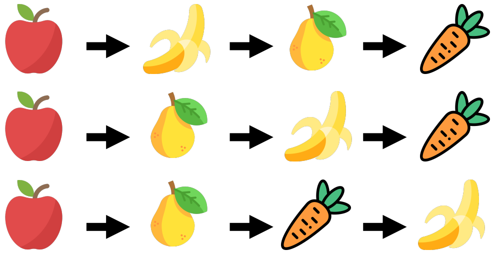
$$f_0 = |C(\mathcal{L}^d)| \geq f_1 \geq f_2 \geq \cdots \geq f_d = 1$$

No annotation

Complete annotation



k=3 out of d=6 variables are labeled



$$\boldsymbol{f_k = 3}$$

Quantifying Information: Problem Setup

Structure: a vector of random variables: $Y = [Y_1, Y_2, \dots, Y_d]$

Let $\mathcal{L}$ be the label set

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Not all assignments are valid
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k out of d variables are labeled → a subset of $C(\mathcal{L}^d)$

Let $\boldsymbol{f_k}$ **be the size of the feasible subset**

$$f_0 = |C(\mathcal{L}^d)| \geq f_1 \geq f_2 \geq \cdots \geq f_d = 1$$

No annotation

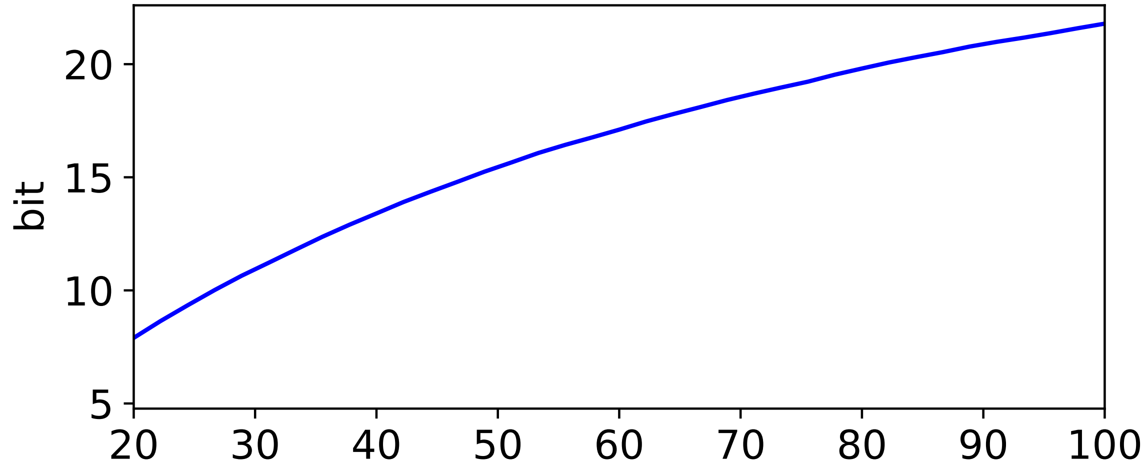
Complete annotation

Define the benefit of k labels: $\boldsymbol{I_k \triangleq \log|C(\mathcal{L}^d)| - E[\log f_k]}$

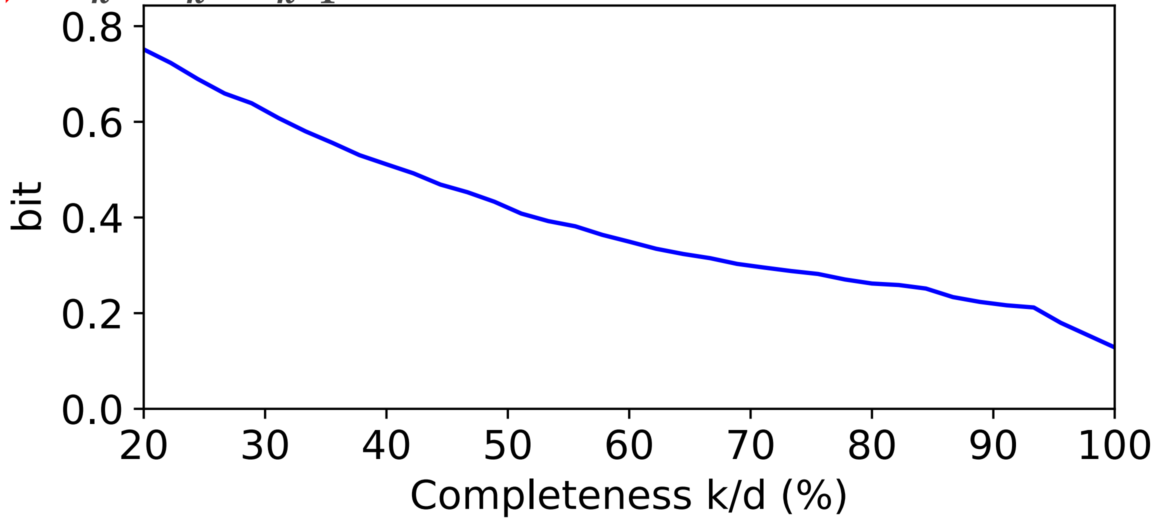
how much of the solution space $C(\mathcal{L}^d)$ has been **disqualified** by k labels

Quantifying Information: I_k for DAG

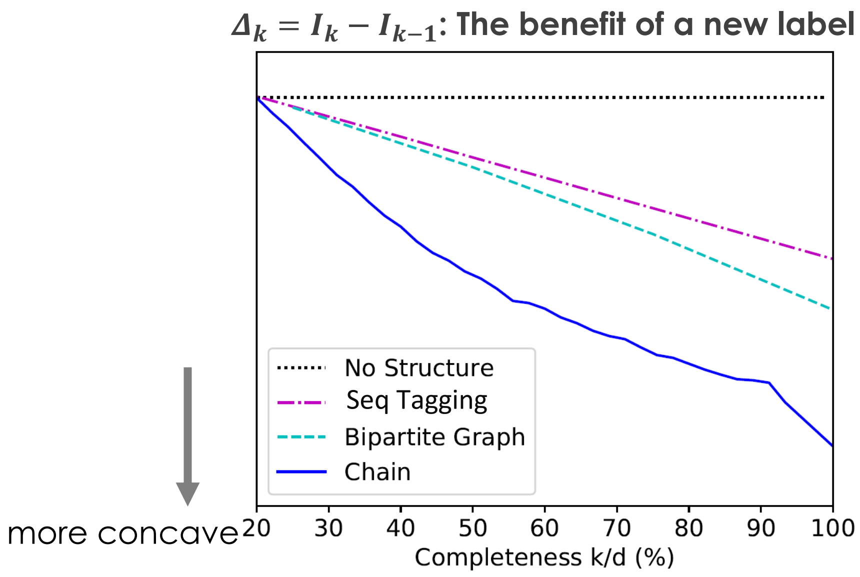
I_k: The benefit of k labels is concave

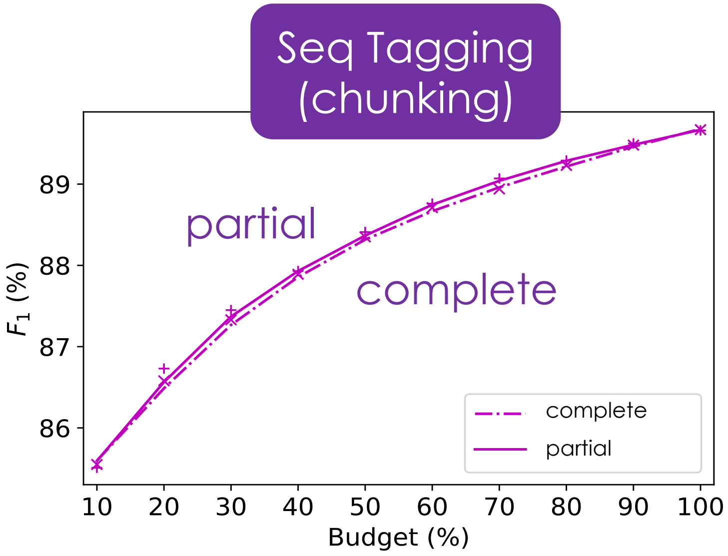


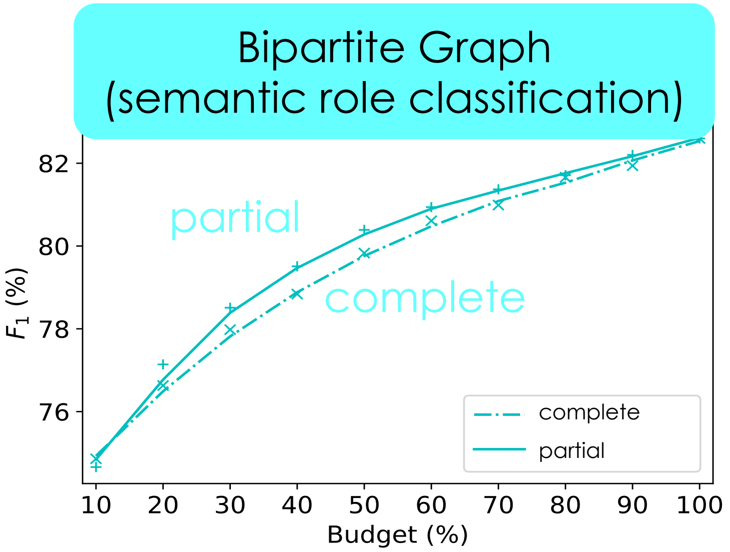
$\Delta_k = I_k - I_{k-1}$: The benefit of a new label is diminishing

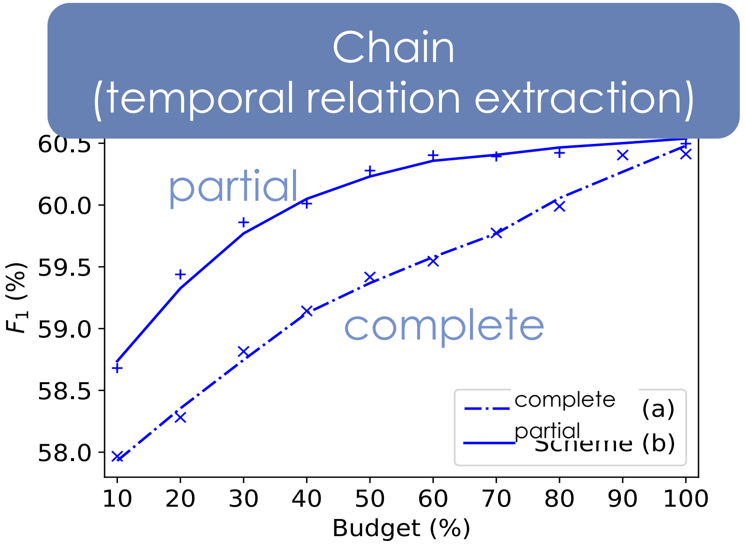


Quantifying Information: Other Types of Structures









What is I_k actually?

Definition: A ***k*-partial annotation** A_k is a vector of random variables $A_k = [A_{k,1}, A_{k,2}, \dots, A_{k,d}] \in (\mathcal{L} \cup \sqcap)^d$, where ⊓ is a special character for no label yet, such that

$\sum_{i=1}^{d} \mathbb{I}(A_{k,i} \neq \sqcap) = k$

$P(Y|A_k = a_k) = P(Y|Y_j = a_{k,j}, j \in \mathcal{J})$, where $\mathcal{J} = \{j: a_{k,j} \neq \sqcap\}$

A_k means k variables in Y are labeled, and those k labels are correct

Theorem: I_k is the mutual information between Y and A_k when both Y and the k variables labeled in A_k follow uniform distributions.

What's annotation?

It is the reduction in the uncertainty of a target Y, by a random process A representing the annotation process

More generally, we argue: any signal that has non-zero mutual information with Y can be viewed as "annotation"

It points out a way to understand and quantify the value of indirect signals.

Measuring the Benefits of Indirect Signals

Foreseeing the Benefits of Incidental Supervision. He et al., EMNLP21.

Can we provide a unified framework for indirect signals, and quantify the extent to which various indirect signals can help the target task?

- Given the task of NER, what types of signals can we use?

PERSON PERSON
Dan tried to stop Bill from getting help for the injured bird .

Gold Annotations

Dan tried to stop Bill from getting help for the injured bird .

Unlabeled texts

PERSON
Dan tried to stop Bill from getting help for the injured bird .

Partial Annotations

PERSON ORG
Dan tried to stop Bill from getting help for the injured bird .

Noisy Annotations

NNP VBD TO VB NNP IN VBG NN IN DT VBN NN .
Dan tried to stop Bill from getting help for the injured bird .

Auxiliary Annotations

O I-ORG
Dan tried to stop Bill from getting help for the injured bird .

Constraints

Same labels in NER

Dan tried to stop Bill from getting help for the injured bird .

Dan gave a book to Jim .

Knowledge

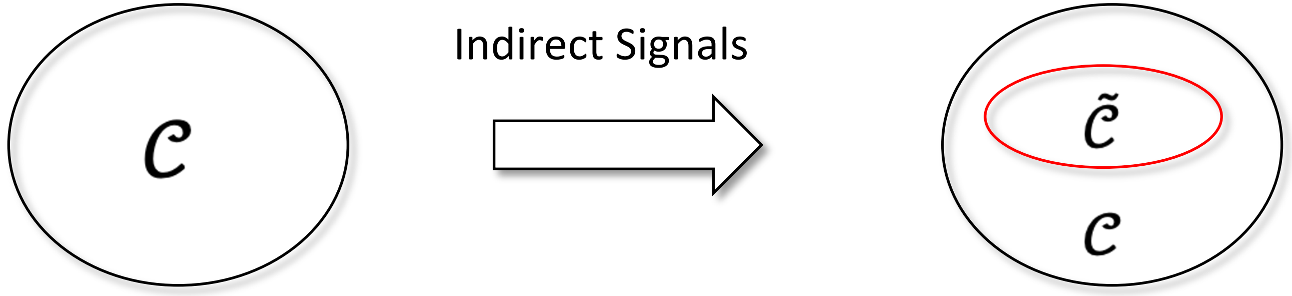
傳達仁PERSON今將執行安樂死，卻突然爆出自己20年前DATE遭緯來體育台ORG封殺，他不懂自己哪裡得罪到電視台。

Cross-lingual Annotations

PABI: Impact of Indirect Signals

- $c: X \to Y, where\ c \in \mathcal{C}$
- Learning theory shows that the size of the concept class determines the "easiness" of the learning problem
  - E.g. the generalization bound $R(c) \le \hat{R}(c) + \sqrt{\frac{\ln|\mathcal{C}| + \ln\frac{2}{\delta}}{2m}}$
- We will show that the use of incidental signals reduces the size of the concept class, and then will use the relative size of the reduction as a measure for the informativeness of the incidental signals

Recall: $I_k \triangleq \log|C(\mathcal{L}^d)| - E[\log f_k]$



Original Concept Class

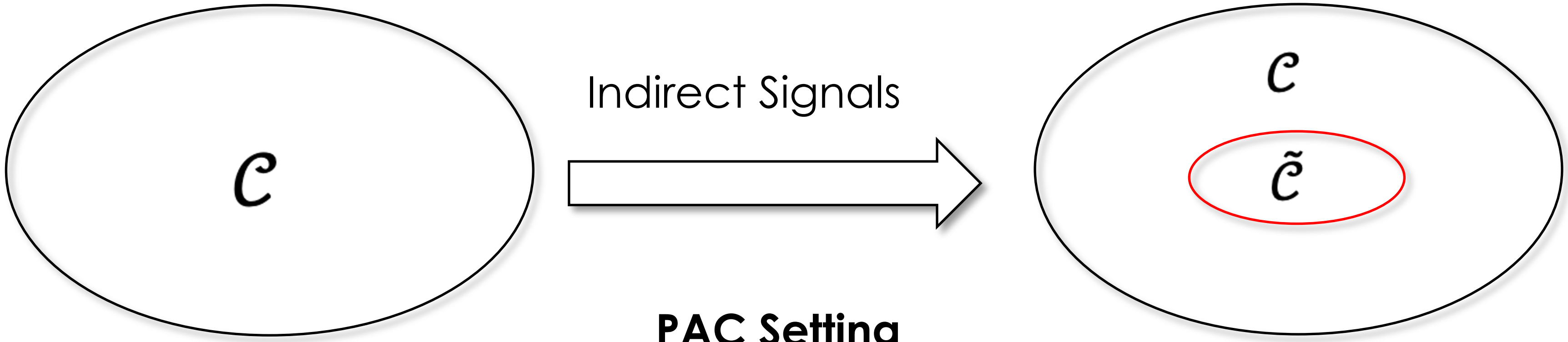
Reduced Concept Class

$$S(\mathcal{C}, \tilde{\mathcal{C}}) = \sqrt{1 - \frac{\ln|\tilde{\mathcal{C}}|}{\ln|\mathcal{C}|}}$$

Smaller $\tilde{\mathcal{C}}$ leads to higher Informativeness S

Reduce the concept class from $\mathcal{C}$ to $\tilde{\mathcal{C}}$

PABI: A Unified PAC-Bayesian Informativeness Measure

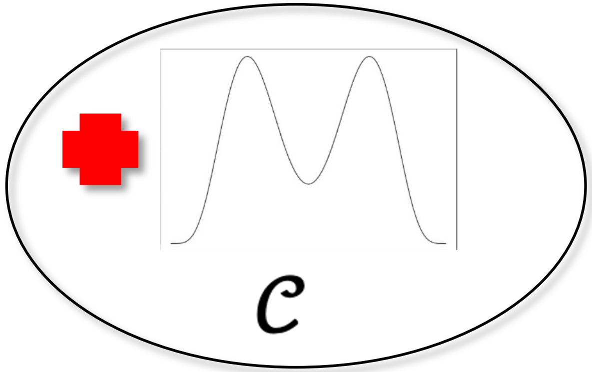


$$S(\mathcal{C},\tilde{\mathcal{C}}) = \sqrt{1 - \frac{\ln|\tilde{\mathcal{C}}|}{\ln|\mathcal{C}|}}$$

PAC Setting

Original Concept Class

Reduce the concept class from $\mathcal{C}$ to $\tilde{\mathcal{C}}$



PAC-Bayesian Setting [1]

$$S'(\pi_0,\tilde{\pi}_0) = \sqrt{1 - \frac{D_{KL}(\pi^*||\tilde{\pi}_0)}{D_{KL}(\pi^*||\pi_0)}} \approx \hat{S}'(\pi_0,\tilde{\pi}_0) = \sqrt{1 - \frac{H(\tilde{\pi}_0)}{H(\pi_0)}}$$

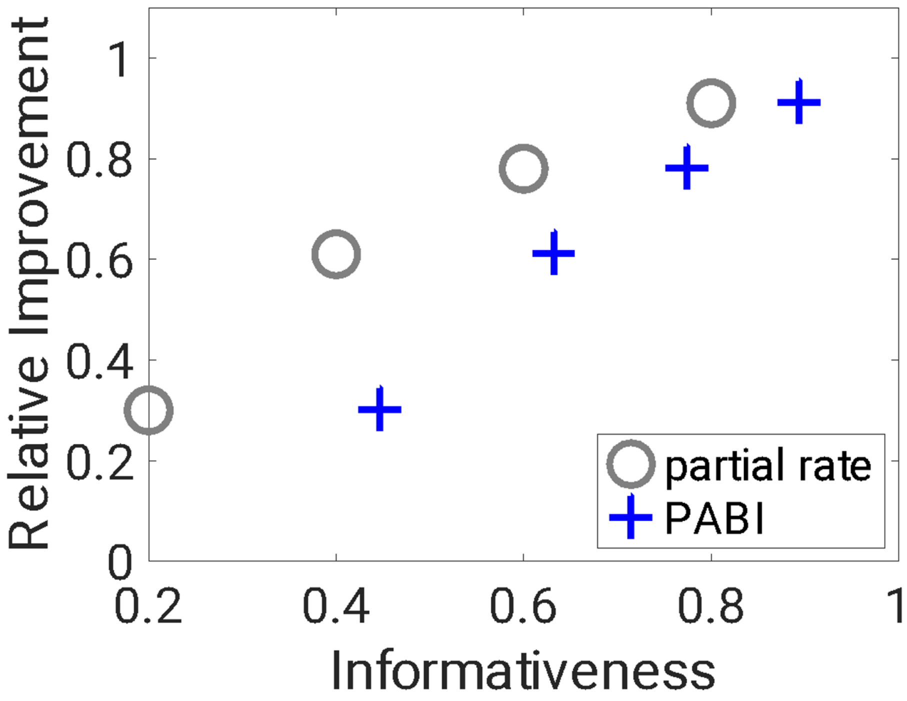
Concept Class with Probability Measure

Make the prior π_0 closer to the gold posterior π^*

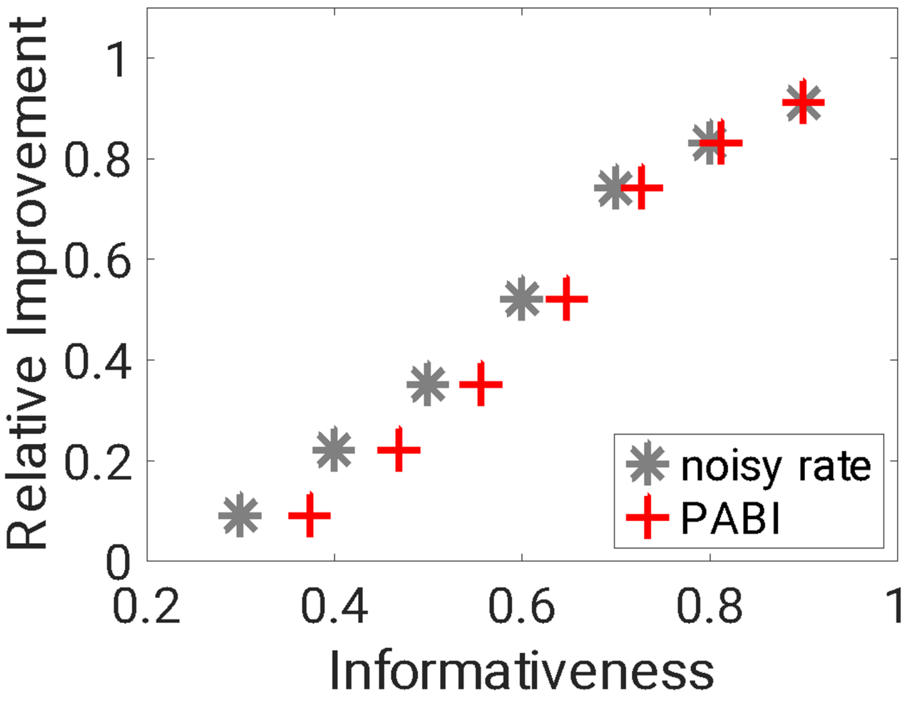
Can handle the infinite concept class case

[1] PAC-Bayesian supervised classification: the thermodynamics of statistical learning. Catoni, 2007.

Results on NER (Ontonotes 5.0)



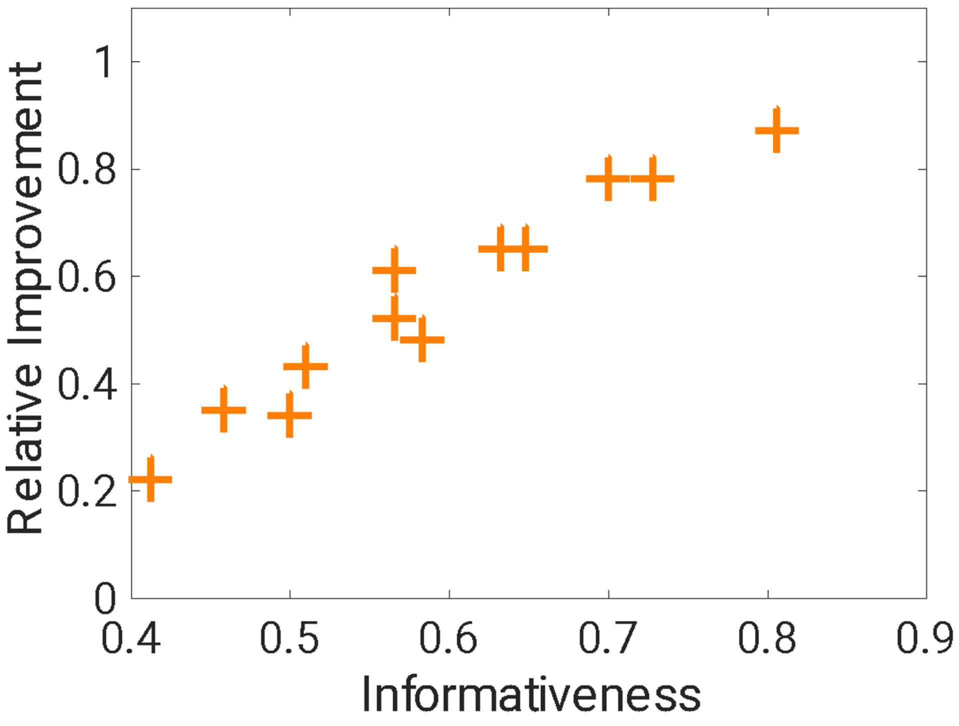
Partial supervision: relative improvement vs. the PABI score for partial signals with different partial rates



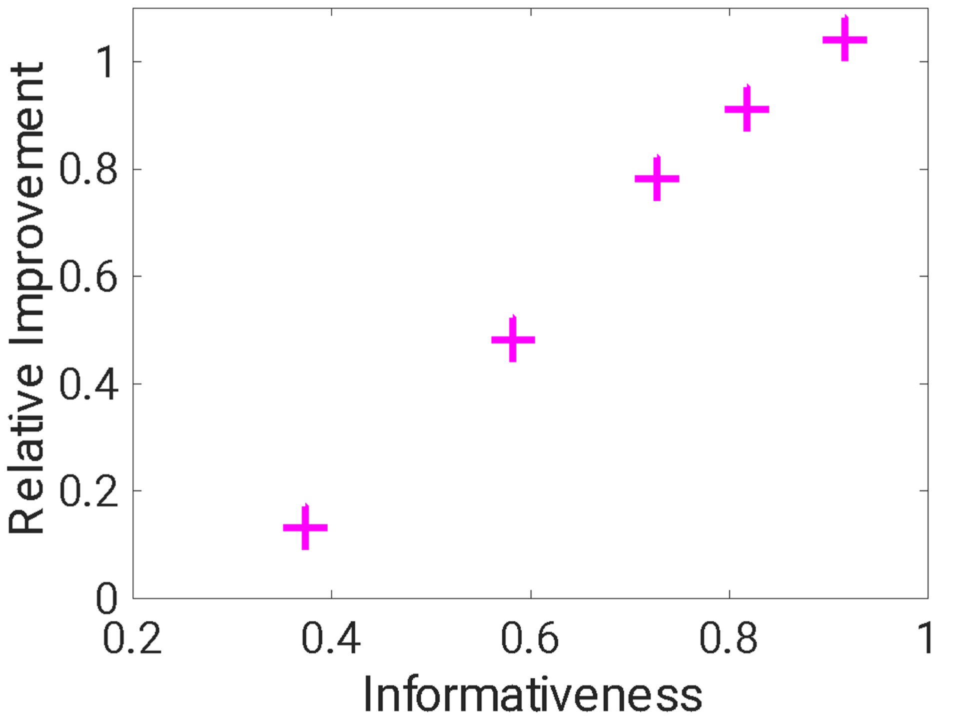
Noisy supervision: relative improvement vs. the PABI score for noisy signals with different noise rates

Before PABI, one might use partial annotation rate / noise rate as a proxy for the usefulness of an incidental dataset; it's indeed a good proxy.

Results on NER (Ontonotes 5.0)



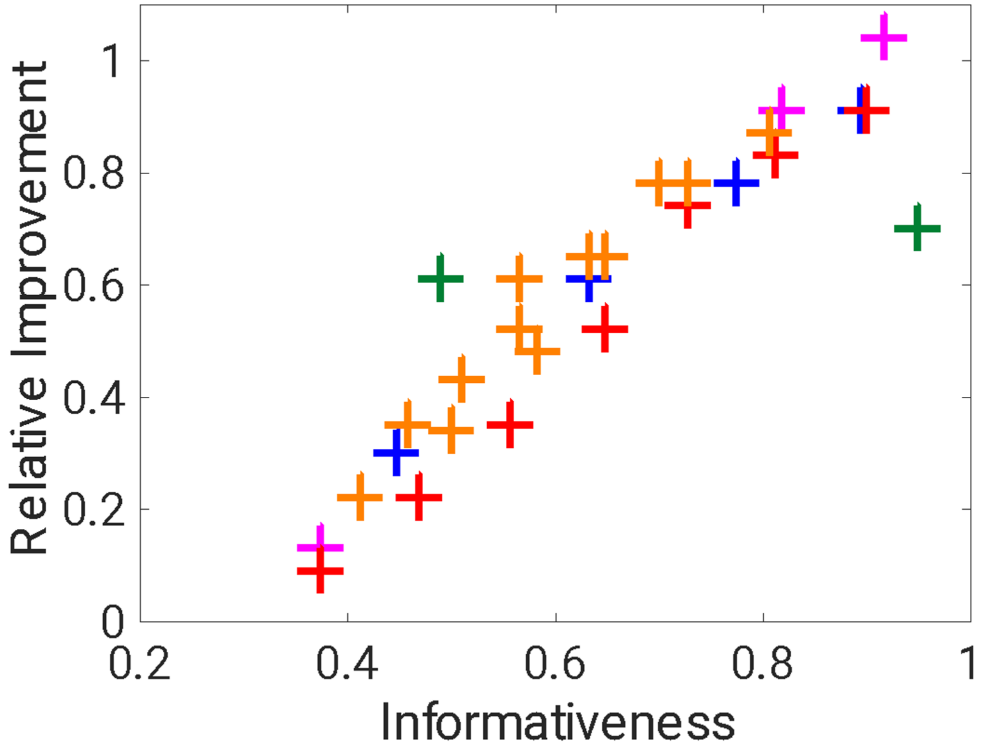
Partial + noisy supervision: relative improvement vs. the PABI score for data with both partial and noisy annotations



Partial + constraints supervision: relative improvement vs the PABI score for data with both partial labels and constraints

However, the (relative) benefits from the mixed signals (e.g., a dataset is both partial and noisy) cannot be determined in existing frameworks, this is where our PABI framework helps.

Results on NER (Ontonotes 5.0): Overlay



The relation between the relative improvement and PABI for various indirect signals: partial labels, noisy labels, auxiliary labels, partial + noisy, and partial + constraints.

The Pearson's correlation coefficient is: 0.92

The Spearman's rank correlation coefficient is: 0.93

Take away:

The informativeness of a signal predicts the improvement provided by the signal.

Key Insight:

PABI is useful in comparison between the contribution of different types of indirect supervision signals.

Study of Learnability

Learnability with Indirect Supervision Signals. Wang et al., NeurIPS20.

Recap

- To move one-step further in theoretical analysis, we consider a classification task where we predict the target label Y of an instance variable X.
- An *indirect supervision signal* is any random variable (denoted by O) that is correlated to the target label Y.
- We assume the learner only receives samples of (X, O) but does not observe Y directly.

Taking the named entity recognition (NER) tagging as an example:

	Instance X	Warren	lives	in	New	York
	Gold label Y	B-PER	O	O	B-LOC	I-LOC
Indirect signals	O_1	B-PER	O	?	?	I
	O_2	NNP	VBZ	IN	NNP	NNP
	O_3	Two of the five labels are "O"				

Intuition

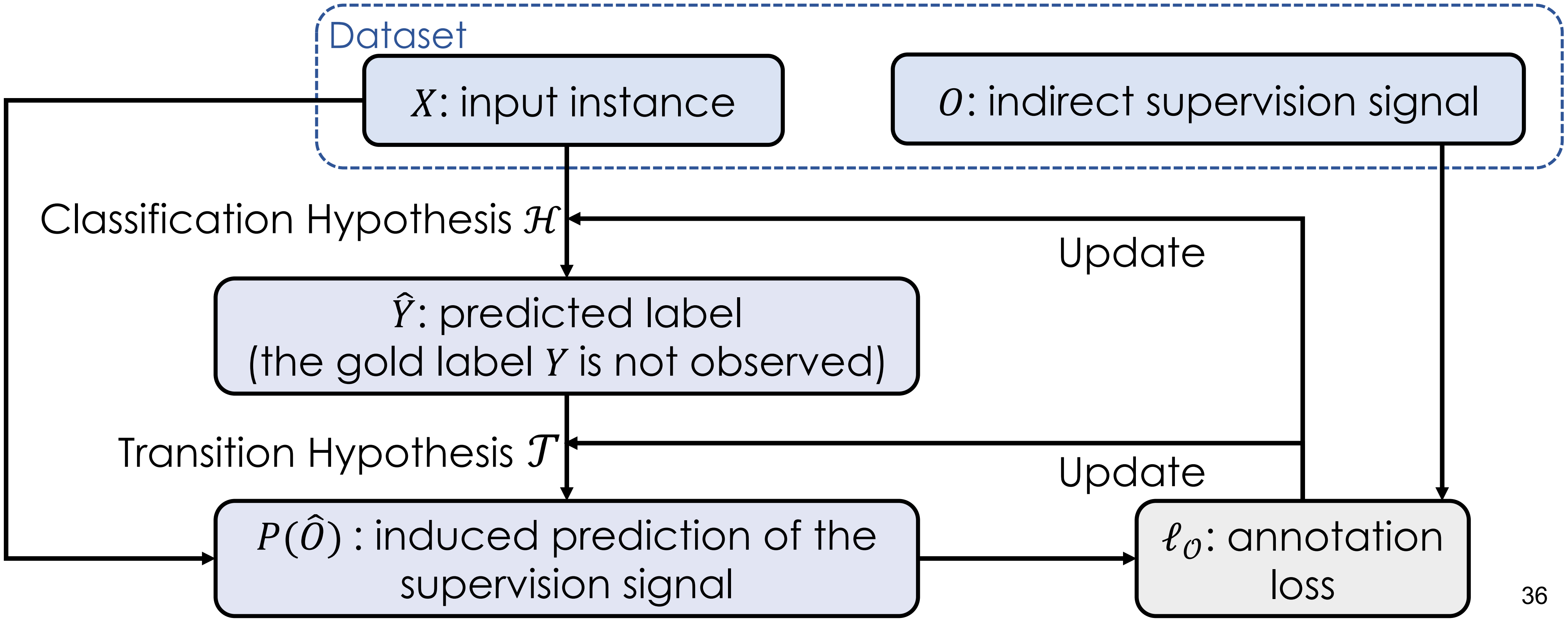
The learnability problem concerns whether we can learn the optimal classifier in our model given sufficient indirect supervision samples.

- Intuitively, some indirect signals cannot guarantee learnability since they are *weak*.
  - For example, O_3 only tells a statistics of the label but there can be a lot of wrong predictions that satisfy this constraint.
  - In contrast, O_1 seems to be a promising choice if the missing rate is low.
- How do we formalize our intuition here?

Instance *X*		Warren	lives	in	New	York
Gold label *Y*		B-PER	O	O	B-LOC	I-LOC
Indirect signals	O_1	B-PER	O	?	?	I
	O_2	NNP	VBZ	IN	NNP	NNP
	O_3	Two of the five labels are "O"				

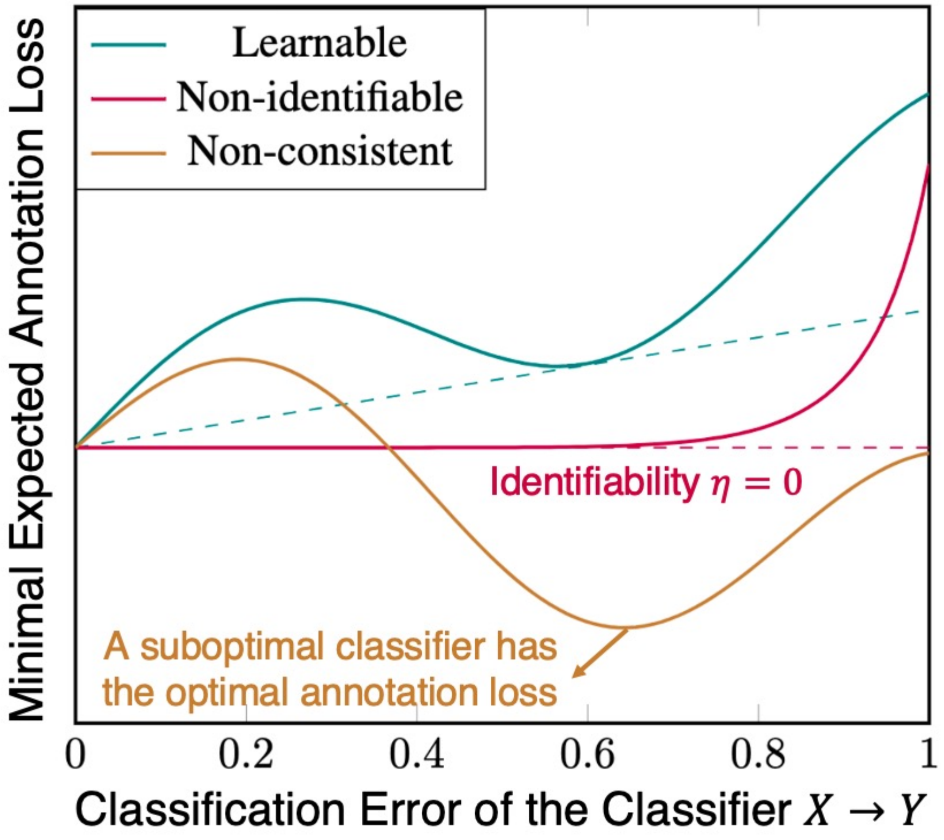
Problem Setup

The learner uses the prediction of Y to induce predictions about O. This prediction is then evaluated by the observed dataset. The annotation loss is used to update the classifier and the transition hypothesis.

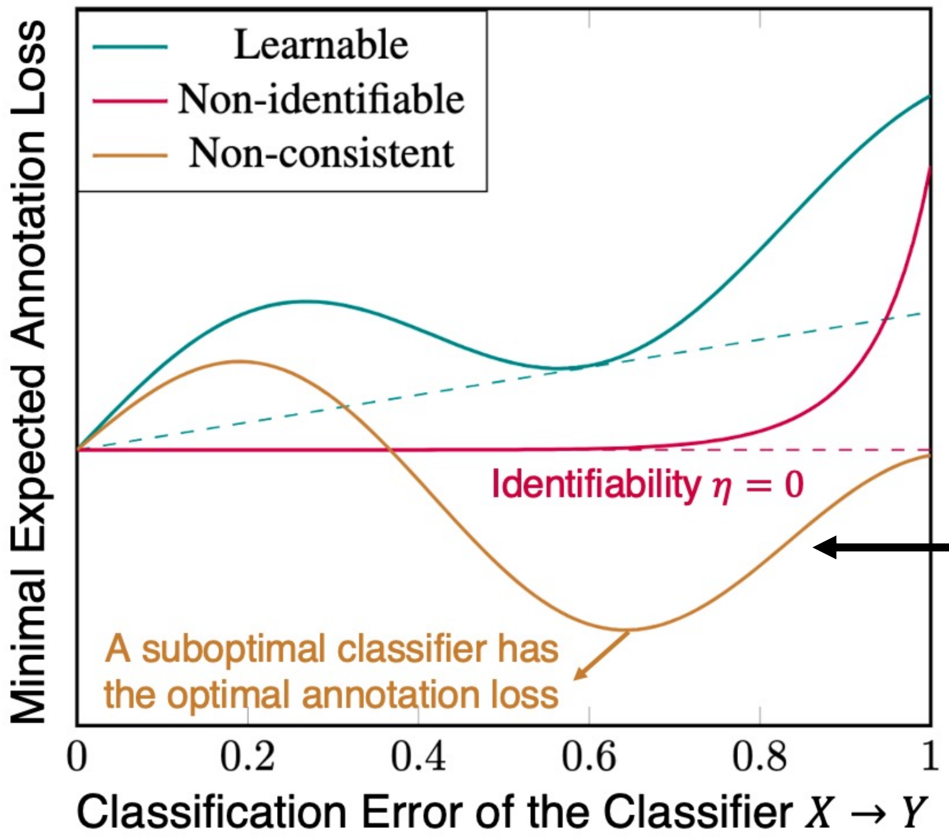


Learnability Condition: Illustration

To illustrate the learnability condition, we plot the the relationship between the classification error of a hypothesis h and the minimum annotation loss (risk) it can have over choices of transition hypotheses.



Learnability Condition 1: Consistency

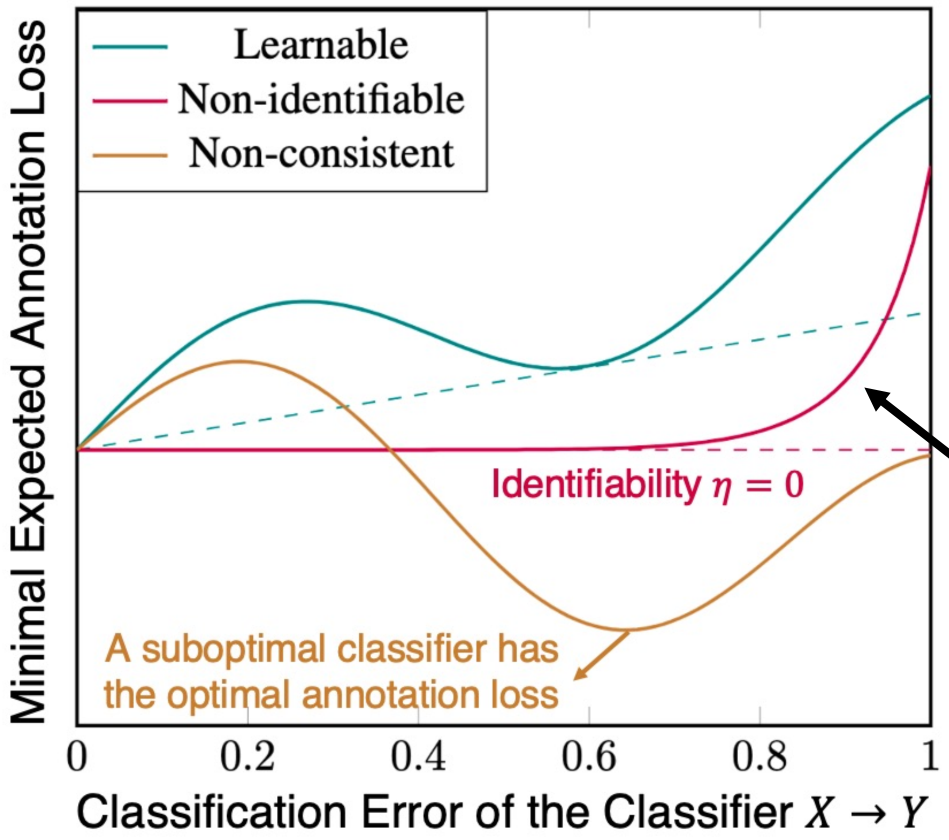


The optimal classifier should be able to induce an optimal prediction of the indirect signal. Formally, we require:

Condition 1

The optimal classifier $h_0 \in \underset{h \in \mathcal{H}, T \in \mathcal{T}}{\operatorname{argmin}} \operatorname{Risk}_{\mathcal{O}}(T \circ h)$.

Learnability Condition 2: Identifiability



A suboptimal classifier should induce a strictly higher annotation loss than the lowest annotation loss on average. Formally, we require

Condition 2

Define and let

$$\eta := \inf_{h \in \mathcal{H}, T \in \mathcal{T} : R(h) > 0} \frac{\text{Risk}_{\mathcal{O}}(T \circ h) - \inf_{T \in \mathcal{T}} \text{Risk}_{\mathcal{O}}(T \circ h_0)}{\text{Risk}(h)} > 0$$

Learnability Condition 3: Complexity

The model should be "simple." Complexity of a model can be described by (a generalized) VC-dimension. Formally, we require:

Condition 3

We assume $\ell_{\mathcal{O}} \circ \mathcal{T} \circ \mathcal{H}$ is weak VC-major with dim $d < \infty$.

Learning Bound

Now we are able to state the main result:

Theorem (Learnability)

If the above three conditions are satisfied, then for any $\delta < 1$, with probability of at least $1-\delta$, we have:

$$\mathrm{Risk}(\mathrm{ERM}(S^{(m)})) \leq \frac{2b}{\eta}\left(\sqrt{\frac{2\overline{\Gamma}_m(d)}{m}} + \frac{4\overline{\Gamma}_m(d)}{m} + \sqrt{\frac{2\log(4/\delta)}{m}}\right)$$

where $\overline{\Gamma}_m(d)$ is defined as

$$\overline{\Gamma}_m(d) := \log\left[2\sum_{j=0}^{\min\{d,m\}}\binom{m}{j}\right] = d\log m(1+o(1)) \text{ as } m \to \infty$$

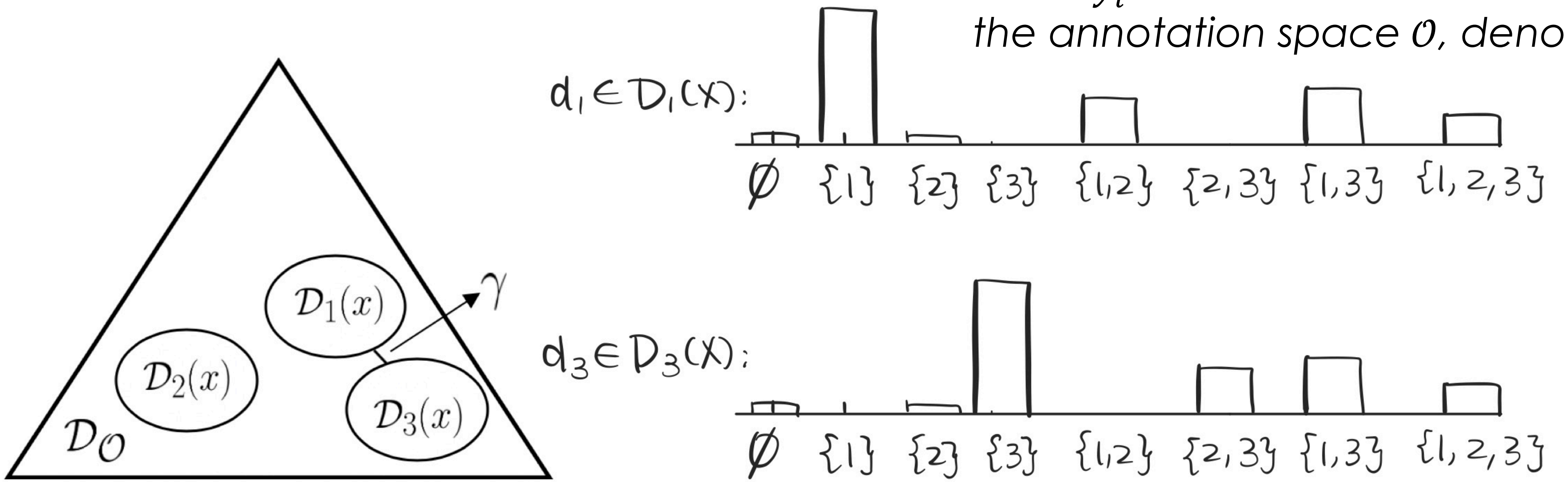
This implies $R(\mathrm{ERM}(S^{(m)})) \to 0$ in probability as $m \to \infty$.

In other words, we can find the optimal classifier as we have a large training set.

Separation

To check the first two conditions more conveniently, we further propose the **separation** condition. We illustrate the definition using the example of partial label O for a 3-class classification problem where O is annotated as a subset of the label space {1,2,3}.

Label y_i will induce a distribution family on the annotation space $\mathcal{O}$, denoted as $\mathcal{D}_i(x)$.



Separation condition requires that different families be separated by a minimal *distance* $\gamma > 0$.

Separation: Formal Definition

Theorem (Separation)

For all $x \in \mathcal{X}$, we denote the induced distribution families by label y_i as $\mathcal{D}_i(x) = \{(T(x))_i : T \in \mathcal{T}\} \subseteq \mathcal{D}_{\mathcal{O}}$, and the set of all possible predictions of y as $\mathcal{H}(x) = \{h(x) : h \in \mathcal{H}\} \subseteq \mathcal{Y}$. If

$$\gamma = \inf_{(x,i,j):p(x,y_i)>0, j \neq i, y_j \in \mathcal{H}(x)} \mathrm{KL}(\mathcal{D}_i(x) \,\|\, \mathcal{D}_j(x)) > 0 \tag{1}$$

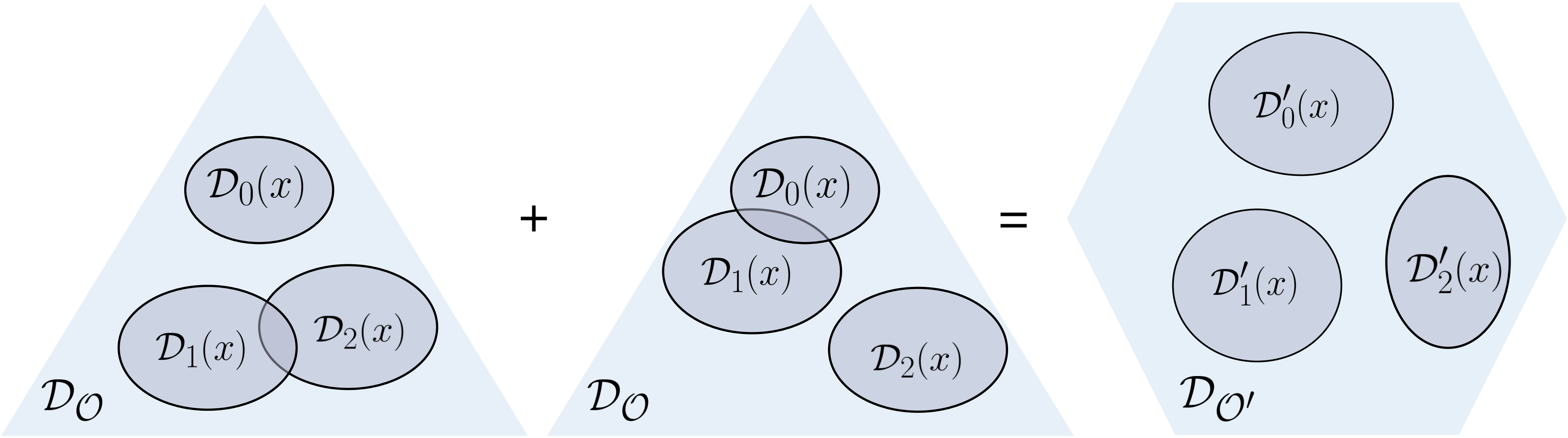
Then the first two conditions are satisfied with $\eta \geq \gamma > 0$ via the ERM of the cross-entropy loss for the observables.

** Moreover, if Eq. (1) is not satisfied, then it can be shown that the learning problem can be arbitrarily difficult since different labels can induce arbitrarily similar distributions over annotation space $\mathcal{O}$. In other words, the observation of $\mathcal{O}$ cannot help us to distinguish different labels.*

Application of Separation: Joint Supervision

If a single source of supervision signal cannot ensure learnability, it should be used jointly with other signals. We show that a joint supervision can:

- Possibly preserve the pairwise separation if modeled *properly*. This effect is visualized in the following figure, where each signal cannot separate one pair of labels, but can be combined to ensure global separation.



Summary

Summary

- We started with a toy example of DAG
  - Knowing part of a graph gives us information about the remaining of the graph
  - We used mutual information as a measure and demonstrated that partially annotating structured prediction problems led to better learning performance, because the uncertainty reduction was higher.
- We continued to argue that indirect signals are those that have non-zero mutual information with the label of the target task.
  - This is supported in PAC and PAC-Bayesian theory because the reduction of uncertainty is actually a term in generalization bounds.
  - We defined PABI as a measure of usefulness of an indirect supervision dataset, and demonstrated its prediction power for actual performance gain on various NLP tasks.
- We formally introduced the learnability conditions from indirect signals, and described a more convenient notion called “separation.”

Thank You