

Selective Generation for Controllable Language Models

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★ NeurIPS 2024 Spotlight Paper



Selective Classification

Motivation

$$f_{\text{cat}} \left\{ \text{dog} \right\} < \tau \implies \text{Reject!}$$

- Selective classification is a **certified** risk control method, which rejects instances as needed, to grant a **desired risk** ε with **high probability** $1 - \delta$.

Why Selective Classification?

Motivation

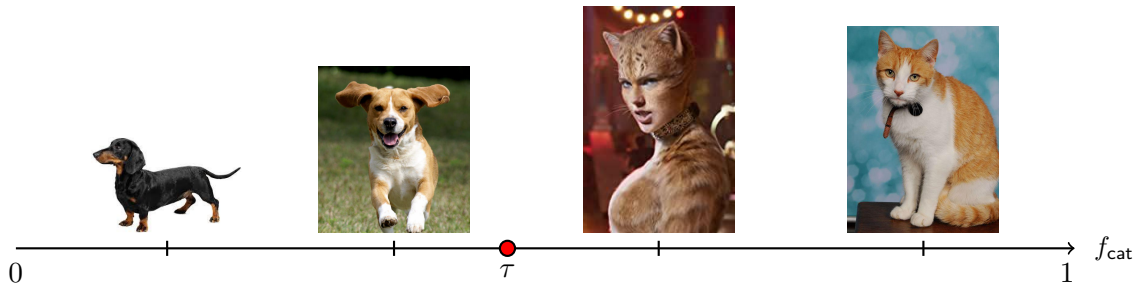
Training Phase



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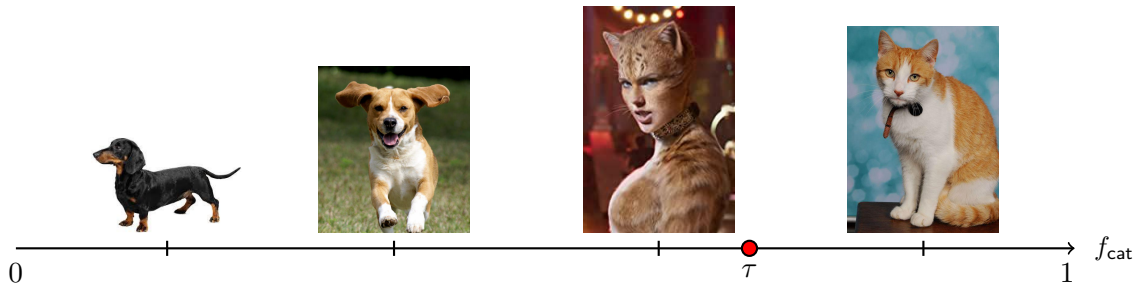
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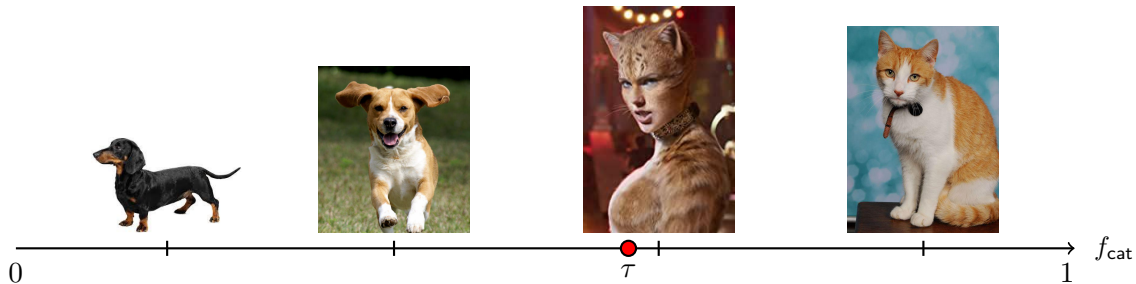
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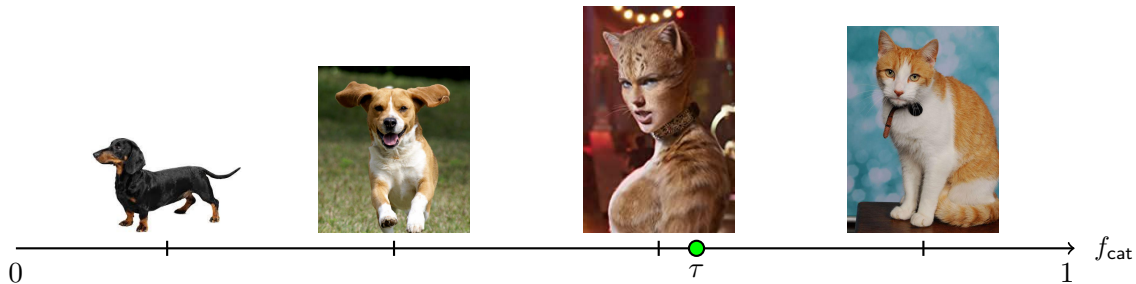
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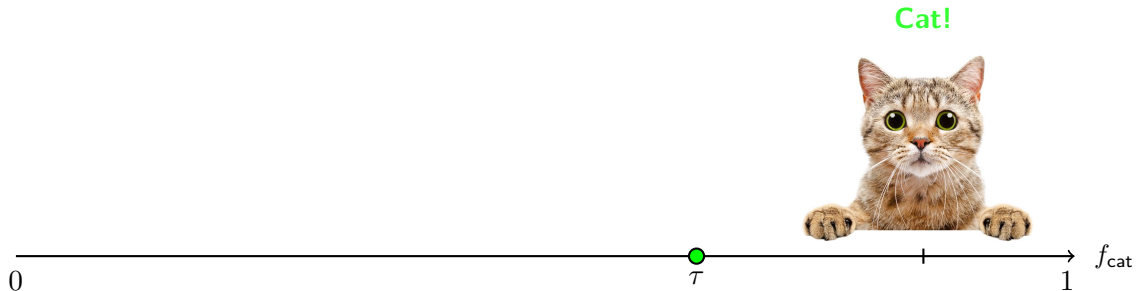
Inference Phase



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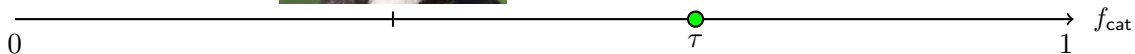
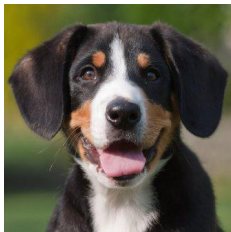
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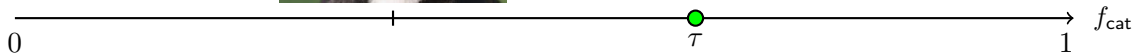


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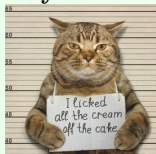
Why Textual Entailment?

Motivation

Classification

T : Classify the image below.

$\hat{y} = \text{cat}$



, $y = \text{cat}$

- ▶ **Selective prediction** is also important to be applied to **generative tasks**.
- ▶ However, unlike exact match (EM) in **classification**, it is difficult to define a **correctness metric**.

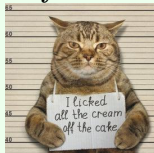
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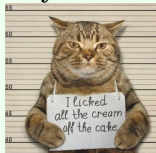
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T : What is the objective of tour de france?

$\mathcal{Y} = \left\{ \begin{array}{c} \text{bike race} \\ \text{cycle race} \\ \text{biking competition} \\ \text{to pick the best cyclist} \\ \vdots \end{array} \right\}, y = \text{bicycle race}$

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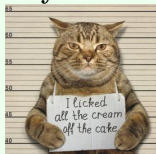
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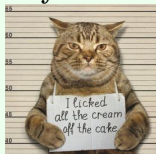
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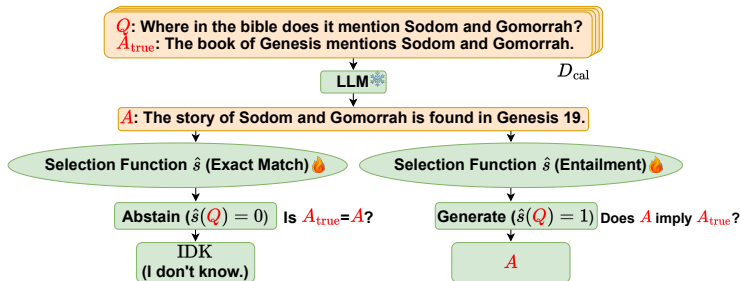
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- ▶ However, unlike exact match (EM) in **classification**, it is difficult to define a **correctness metric**.

$\implies$ We employ **textual entailment**: $E_{\text{true}}(y) := \{\hat{y} \in \mathcal{Y} \mid \hat{y} \text{ implies } y\}$.

Why Semi-Supervised Learning?

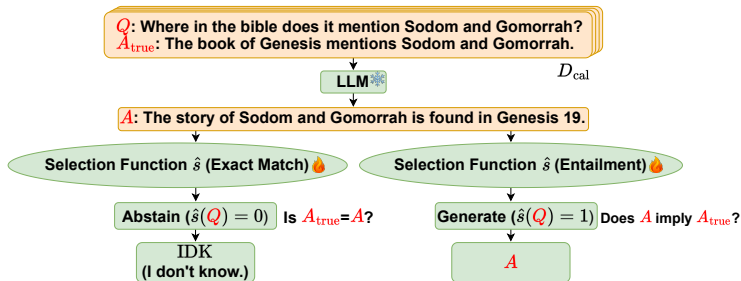
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- ▶ We can avoid *metric misalignment* in generation by leveraging entailment.
- ▶ However, labeling is expensive.

Why Semi-Supervised Learning?

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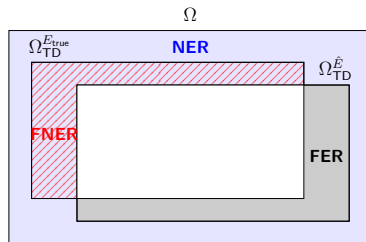


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- ▶ However, labeling is expensive.

⇒ We leverage question-answering pairs without entailment via **semi-supervised learning (SSL)**.

FDR-E Bound (1)

Method

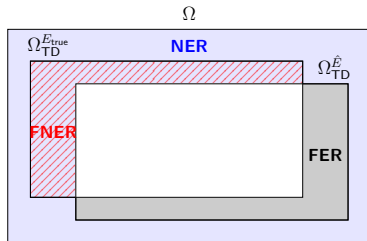


With the previously defined **textual entailment** $E_{true}(\mathbf{y})$, We can define **FDR-E**, the false discovery rate with respect to the textual entailment relation, as follows:

$$\mathbb{P}\{G(\mathbf{x}) \notin E_{true}(\mathbf{y}) \mid \hat{S}(\mathbf{x}) \neq \text{IDK}\}$$

FDR-E Bound (2)

Method

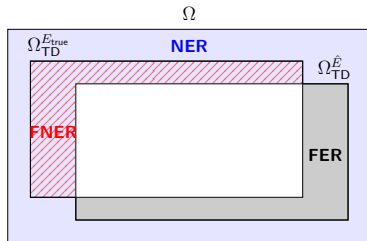


In the SSL setup, the FDR-E can be decomposed as follows:

$$\underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{G(\mathbf{x}) \notin E_{\text{true}}(\mathbf{y})\}}_{(A)} = \underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{v = 1\}}_{(B)} \underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{e = 0\}}_{(C)} + \underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{v = 0\}}_{(D)} \underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{e = 0\}}_{(E)}$$

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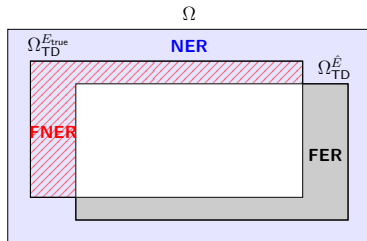


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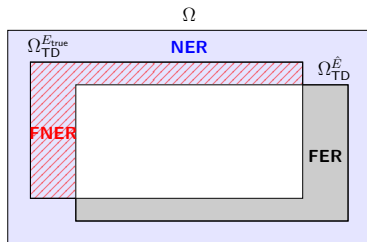


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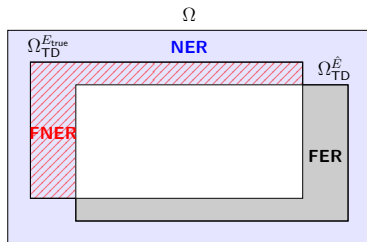


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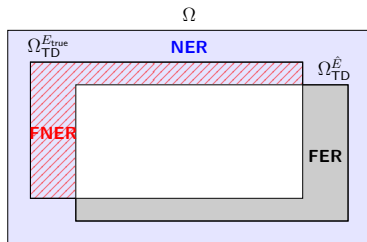
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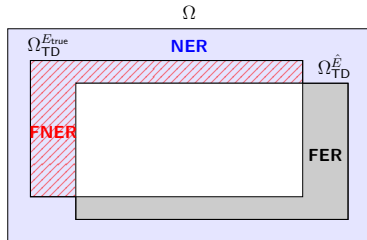


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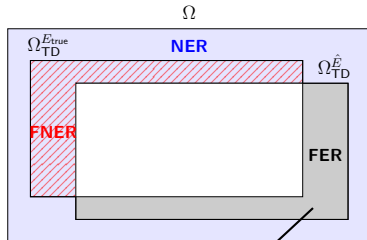
Lemma 1

(E) is decomposed as follows:

$$\underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{e = 0\}}_{(E)} = \underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{e = 0, \hat{e} = 1\}}_{FER} - \underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{e = 1, \hat{e} = 0\}}_{FNER} + \underbrace{\mathbb{P}_{\mathcal{D}_{\hat{S}}}\{\hat{e} = 0\}}_{NER}.$$

FDR-E Bound (2)

Method



Lemma 1

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FDR-E Bound (3)

Method

Entailment Set Learning

$\mathcal{A}_{\text{FER}}$ returns $\hat{E}$ which controls the **FER** of pseudo-labeled examples, *i.e.*,

$$\mathbb{P}\{\mathcal{R}_{\text{FER}}(\hat{E}) \leq \varepsilon_E\} \geq 1 - \delta_E.$$

- ▶ We use $\hat{E}$ as a pseudo-labeling function for SSL – see our paper!

Lemma 2

If $\hat{E} := \mathcal{A}_{\text{FER}}(\hat{\mathbf{Z}}_E)$ satisfies the above guarantee, we have

$$\mathbb{P}_{\mathcal{D}}\{e = 0\} \leq \varepsilon_E - L_{\text{Binom}}(\hat{k}; |\hat{\mathbf{Z}}_E|, \delta'_E/2) + U_{\text{Binom}}(\hat{l}; |\hat{\mathbf{Z}}_U|, \delta'_S) =: U_{\text{SSL}}$$

- ▶ We find an optimal ε_E that minimizes U_{SSL} , resulting $U_{\text{SSL}}^{\text{OPT}}$ – see our paper!

Controllable Guarantee

Method

Algorithm

Our **semi-supervised** method $\mathcal{A}_{\text{SGen}}^{\text{Semi}}$ solves the following optimization problem:

$$\text{find}_{\hat{S} \in \mathcal{H}} \hat{S} \quad \text{subj. to} \quad w_{\text{SL}} U_{\text{SL}} + w_{\text{SSL}} U_{\text{SSL}}^{\text{OPT}} \leq \varepsilon_S$$

Theorem 1

$\mathcal{A}_{\text{SGen}}^{\text{Semi}}$ satisfies the following controllable guarantee on the FDR-E, i.e.,

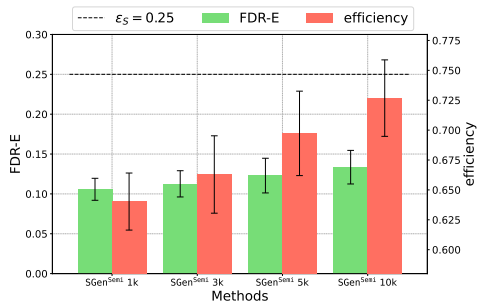
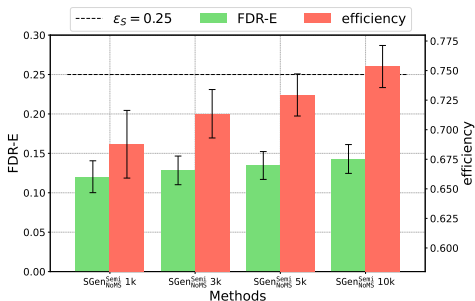
$$\mathbb{P} \left\{ \mathbb{P} \{ G(\mathbf{x}) \notin E_{\text{true}}(\mathbf{y}) \mid \hat{S}(\mathbf{x}) \neq \text{IDK} \} \leq \hat{U} \right\} \geq 1 - \delta.$$

Experiment

Question x	Who is the actor who plays Draco Malfoy?	When did the movie Benjamin Button come out?
Correct Answer y	Thomas Andrew Felton plays Draco Malfoy in the Harry Potter movies.	The movie Benjamin Button come out December 25, 2008
Generated Answer $G(x)$	The actor who plays Draco Malfoy is Tom Felton. (correct)	The movie The Curious Journey of Benjamin Button was released in 2008. (correct)
$S\text{Gen}_{\text{EM}}$	rejected	rejected
$S\text{Gen}^{\text{Semi}}$ (ours)	accepted	accepted

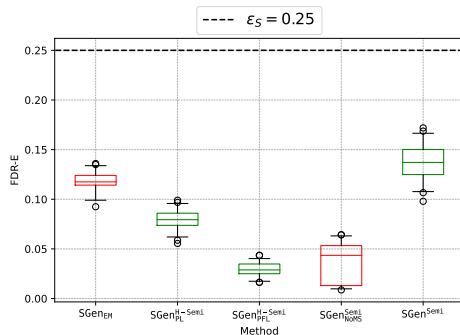
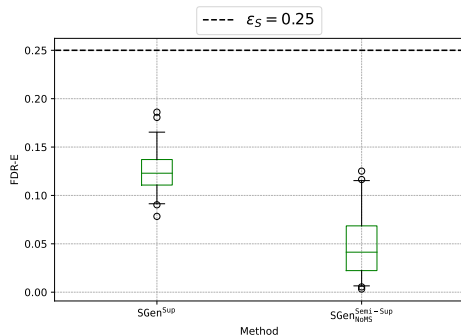
- $S\text{Gen}^{\text{Semi}}$ can capture correctness better than $S\text{Gen}_{\text{EM}}$.

Experiment



- More unlabeled samples are beneficial to achieving better efficiency.

Experiment



- The FDR-E for $\hat{S}$ is well controlled below ϵ_S , desired FDR-E, under the test environment.

Conclusion

- ▶ We leverage logical **entailment** and propose a novel **semi-supervised** learning approach for **selective generation**, demonstrating its *theoretical* and *empirical* efficacy.

