Cold-start Active Learning through Self-supervised Language Modeling

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EMNLP 2020

Active Learning

- **Goal:** Recognize most relevant examples and query their labels from an all-knowing oracle

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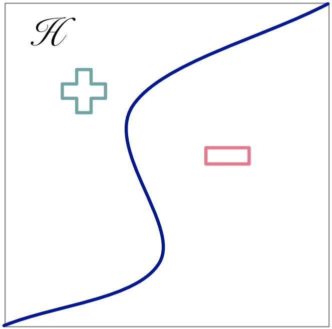
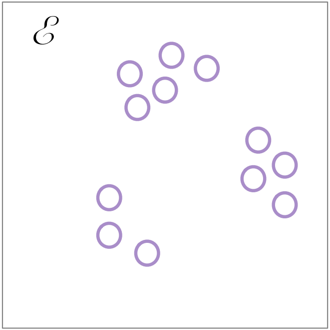
- **Issue:** Traditional active learning works poorly for modern neural networks, especially during *cold-start*
- Limitations in SOTA NLP show a greater need for active learning *and* make active learning more difficult to deploy

Uncertainty–Diversity Dichotomy



Dasgupta (2011)

Uncertainty–Diversity Dichotomy



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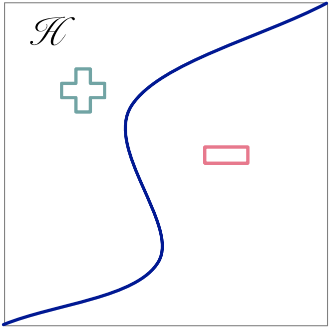
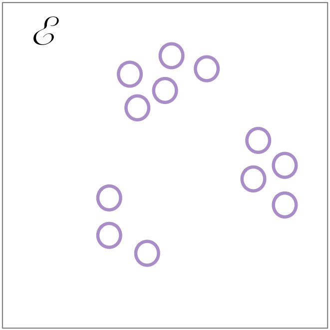
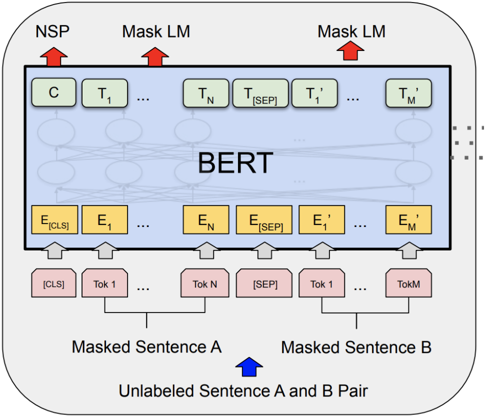




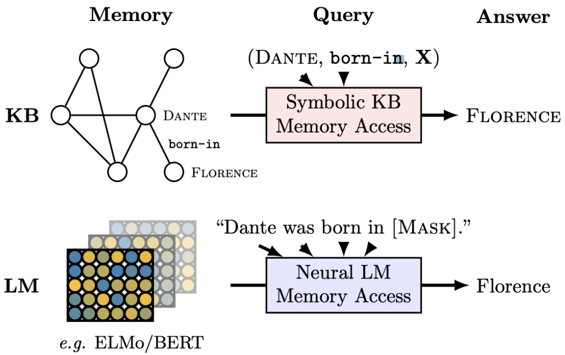
Dasgupta (2011)

Language Model Pre-training



Devlin et al. (2019)

Language Model Pre-training



Petroni et al. (2019)

ALPS

Active **L**earning by **P**rocessing **S**urprisal

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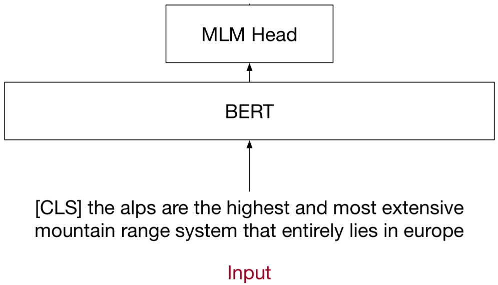
2. Run k-means clustering on the surprisal embeddings
3. Find the sentences that are closest to each cluster center
4. Query labels for these k sentences

Surprisal Embeddings

[CLS] the alps are the highest and most extensive mountain range system that entirely lies in europe

Input

Surprisal Embeddings



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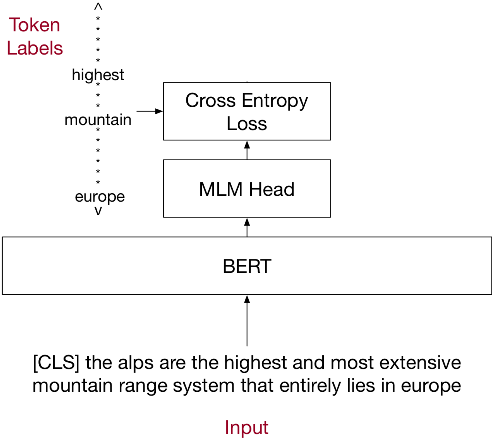

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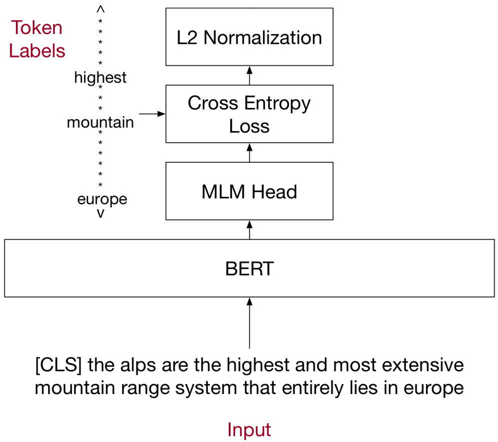

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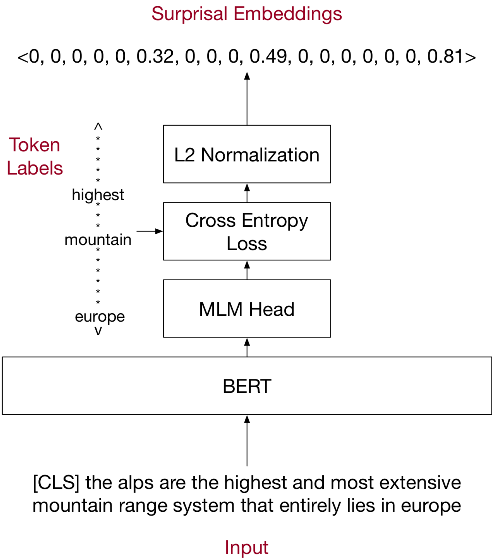

ALPS in Action

```
Emotional eating is associated with
overeating...(background)

Ticagrelor and clopidogrel antiplatelet treatment
were used...(methods)

Visual acuity improvements in the 2 groups were
similar.  (results)

Teacher-rated and self-rated antisocial
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In contrast, early intervention with selective
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$\langle$	0.000	0.000	0.000	0.000	0.021	0.000	0.000	... $\rangle$
$\langle$	0.043	0.000	0.000	0.000	0.000	0.385	0.000	... $\rangle$
$\langle$	0.000	0.000	0.000	0.002	0.000	0.000	0.000	... $\rangle$
$\langle$	0.000	0.000	0.000	0.000	0.000	0.000	0.039	... $\rangle$
$\langle$	0.000	0.001	0.000	0.000	0.000	0.000	0.022	... $\rangle$

...

ALPS in Action

$$\langle \quad 0.000 \quad 0.000 \quad 0.000 \quad 0.000 \quad 0.021 \quad 0.000 \quad 0.000 \quad \ldots \quad \rangle$$

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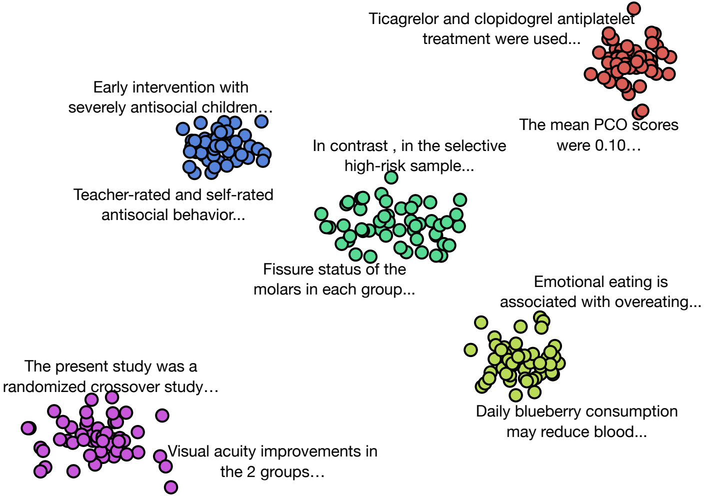
$$\ldots$$

ALPS in Action



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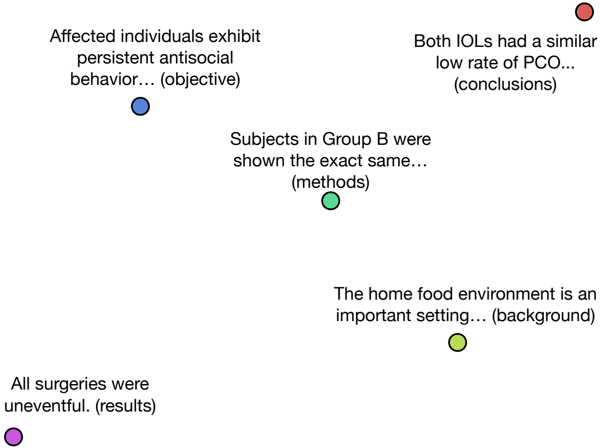

Experiments

- **Task:** PUBMED 20k RCT (Dernoncourt and Lee, 2017)
- **Model:** SCIBERT (Beltagy et al., 2019)
- Simulate active learner for 10 iterations where 100 sentences are sampled each time

Baselines

1. Random

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2. Entropy (Lewis and Gale, 1994)

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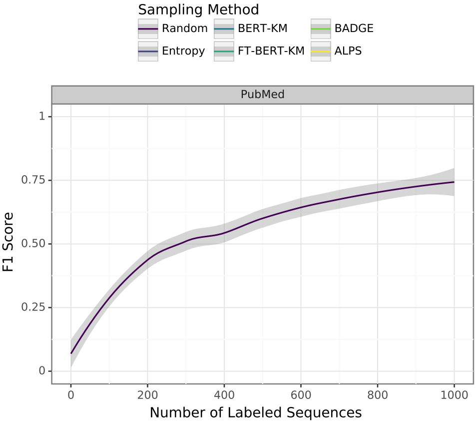
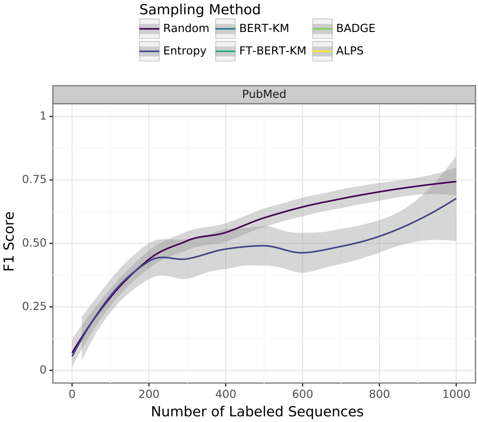
5. FT-BERT-KM

Results



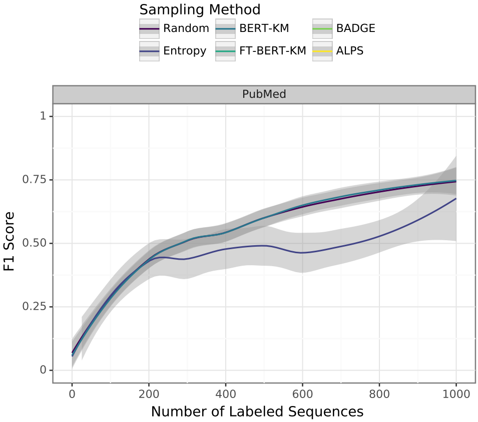
Random

Results



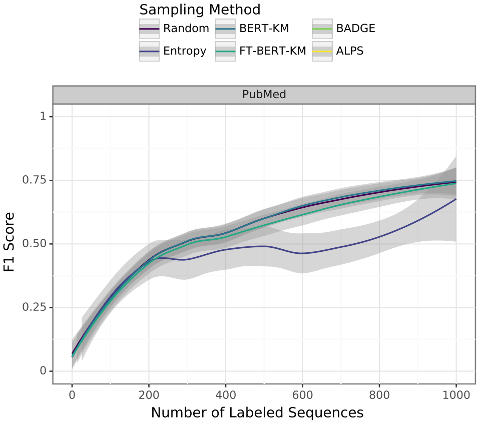
Entropy

Results



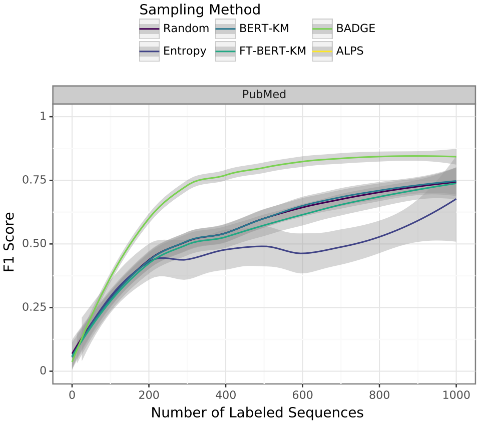
BERT-KM

Results



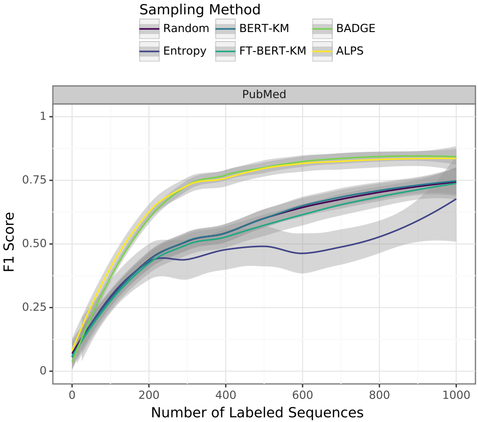
FT-BERT-KM

Results



BADGE

Results



ALPS

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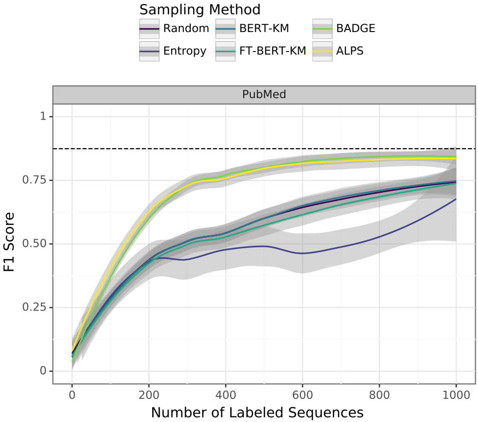

Full training dataset

Time

	AG NEWS	PUBMED
Random	< 1	< 1
Entropy	7	10
ALPS	14	24
BADGE	23	70
BERT-KM	28	58
FT-BERT-KM	33	79

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