Deep Active Learning: Reducing Annotation Effort for Automatic Sequence Tagging of Clinical and Biomedical Texts

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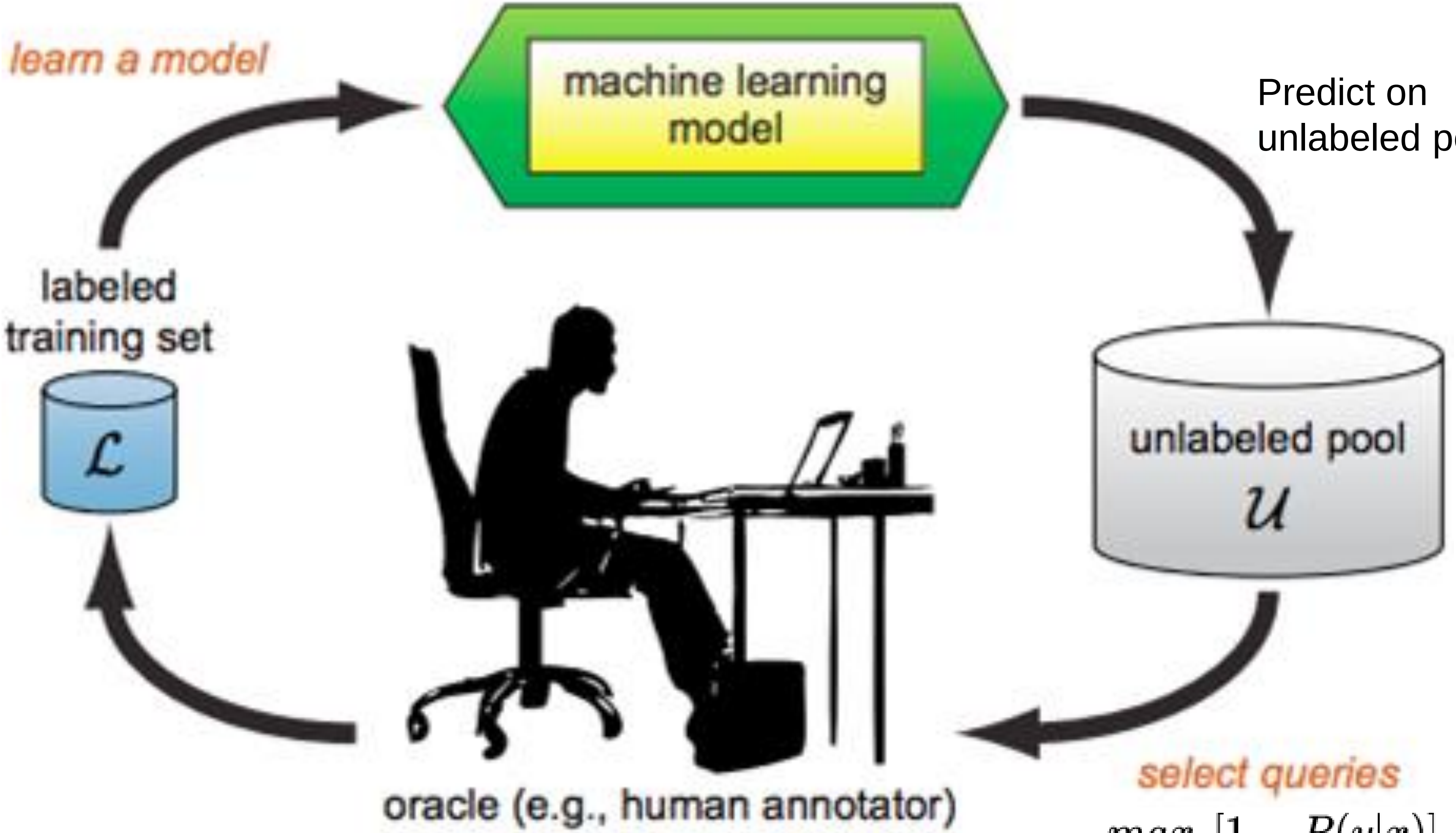
Basic Idea of Active Learning (AL)



Predict on unlabeled pool

$$max_y[1 - P(y|x)]$$

(from Burr Settles et al.)

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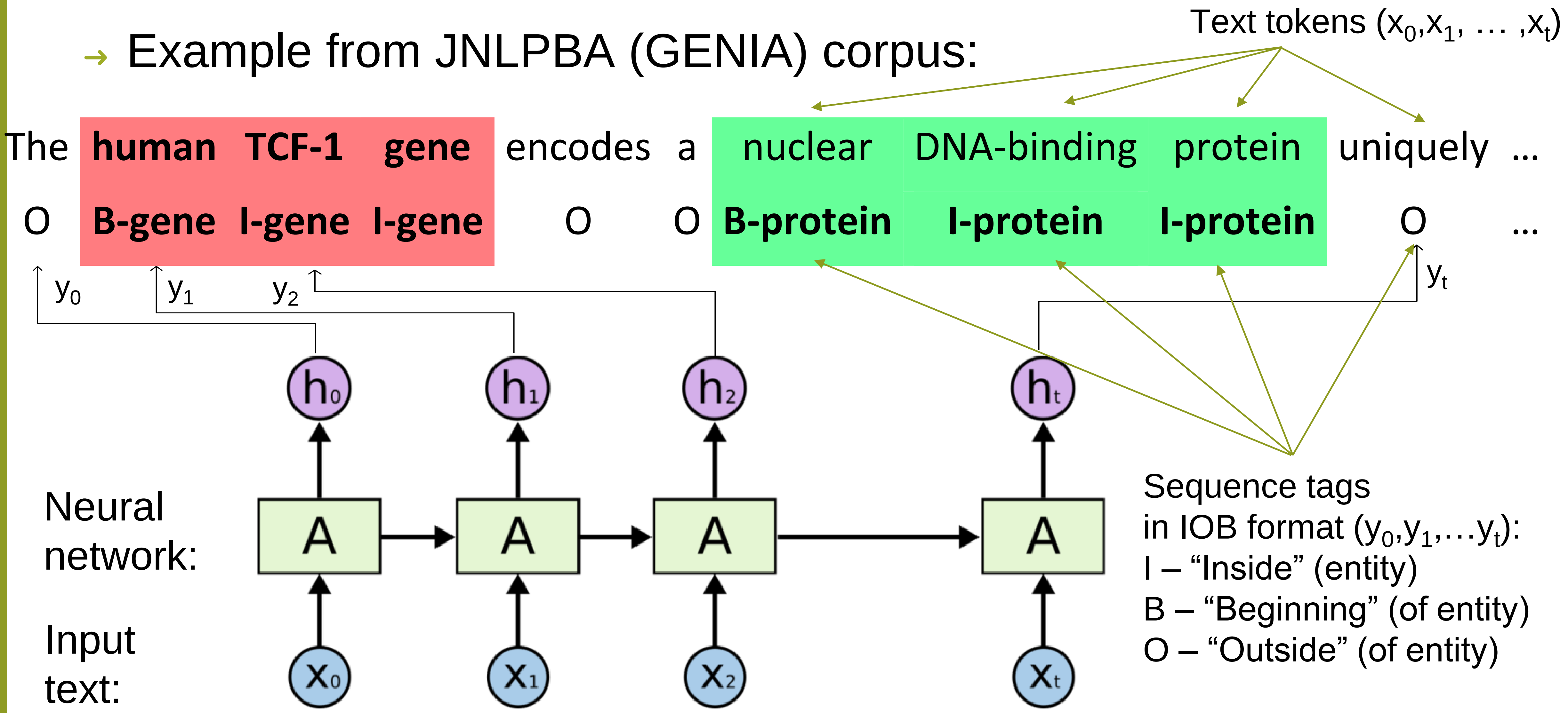
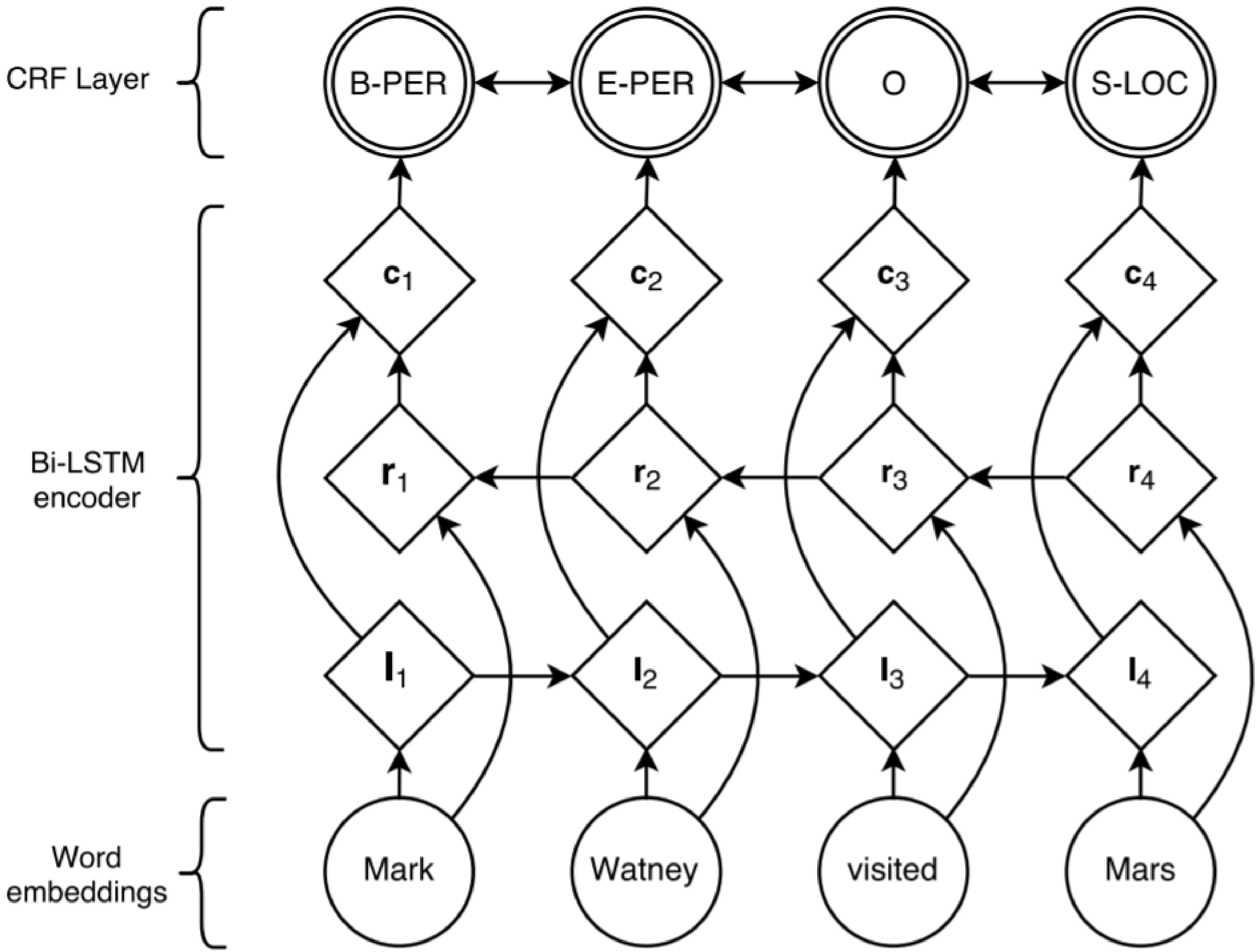
Sequence Tagging Task (NER)

→ Example from JNLPBA (GENIA) corpus:



Popular Architecture



- BiLSTM-CRF (Ma and Hovy, 2016)
- Near SOTA results if accompanied with strong word representations

Classical AL
Query Strategies

Common Query Strategies: Uncertainty Sampling (Lewis and Catlett, 1994)

→ Uncertainty sampling: the learner queries the instance, about which it has the least certainty

Least confidence (McCallum et al., 2005):

$$\phi^{LC}(\mathbf{x}) = 1 - P(\mathbf{y}^*|\mathbf{x};\theta)$$

Margin (Scheffer et al., 2001):

$$\phi^{M}(\mathbf{x}) = -(P(\mathbf{y}_1^*|\mathbf{x};\theta) - P(\mathbf{y}_2^*|\mathbf{x};\theta))$$

Token entropy:

$$\phi^{TE}(\mathbf{x}) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{M} P_\theta(y_t = m)\log P_\theta(y_t = m)$$

N-best sequence entropy (NSE):
(Kim et al., 2006)

$$\phi^{NSE}(\mathbf{x}) = -\sum_{\hat{\mathbf{y}}\in\mathcal{N}} P(\hat{\mathbf{y}}|\mathbf{x};\theta)\log P(\hat{\mathbf{y}}|\mathbf{x};\theta)$$

Common Query Strategies: Query by Committee (Seung et al., 1992)

→ Query-by-committee: a “committee” of models selects the instance about which its members most disagree

Vote entropy (Dagan and Engelson, 1995):

$$\phi^{VE}(\mathbf{x}) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{M}\frac{V(y_t, m)}{C}\log\frac{V(y_t, m)}{C}$$

$V(y_t, m)$ – number of votes for position t and label m

Largest KL-divergence between committee members and consensus (McCallum and Nigam, 1998):

$$\phi^{KL}(\mathbf{x}) = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C}\sum_{c=1}^{C} D\left(\theta^{(c)} \| \mathcal{C}\right)$$

Sequence vote entropy:

$$\phi^{SVE}(\mathbf{x}) = -\sum_{\hat{\mathbf{y}} \in \mathcal{N}^c} P(\hat{\mathbf{y}}|\mathbf{x}; \mathcal{C}) \log P(\hat{\mathbf{y}}|\mathbf{x}; \mathcal{C})$$

Fraction of models that disagree with the most popular choice (Shen et al., 2018):

$$f_i = 1 - \frac{\max_y \left|\left\{m : \operatorname{argmax}_{y'} \mathbb{P}^m[y_i = y'] = y\right\}\right|}{M}$$

See (Settles and Craven, 2008) for further detail

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Problems with QbC and US Methods

- Query-by-committee is slow since you need to train an ensemble of classifiers and perform inference on all of them
- Uncertainty estimates via standard US methods are not very good for unseen regions
- Both US and QbC prone to sample outliers – objects that are useless for training a model

Several SOTA Approaches in DAL for Information Extraction

Shen et al., 2018 (ICLR-2018) (1)

“Deep active learning for named entity recognition” (Shen et al., 2018)

- → First work that uses deep learning model for sequence labeling in conjunction with active learning
- → Propose US strategy Maximum Normalized Log-Probability (MNLP):

$$\phi^{\mathrm{MNLP}}(x) = \max_{\{y_j\}} \frac{1}{n} \sum_{i}^{n} \log P(y_i | \{y_j\} \setminus y_i, \{x_j\})$$

- → Propose CNN-CNN-LSTM architecture (CNN character encoder, CNN token encoder, LSTM decoder), argue that it is faster than alternatives like LSTM-LSTM-CRF

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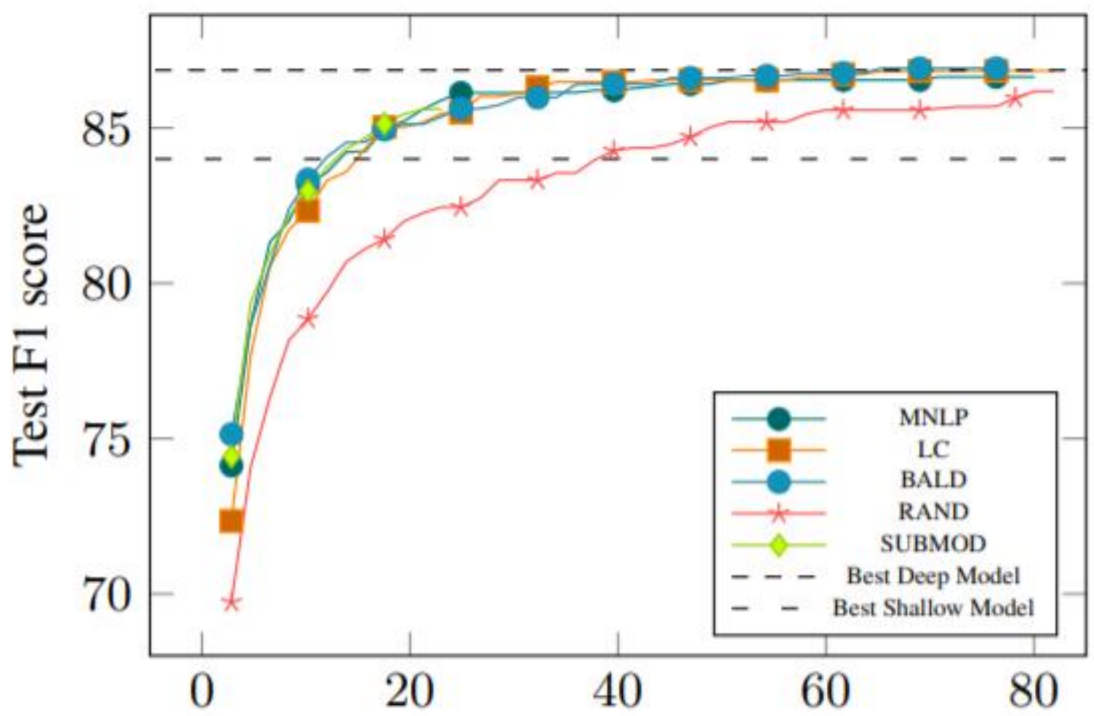
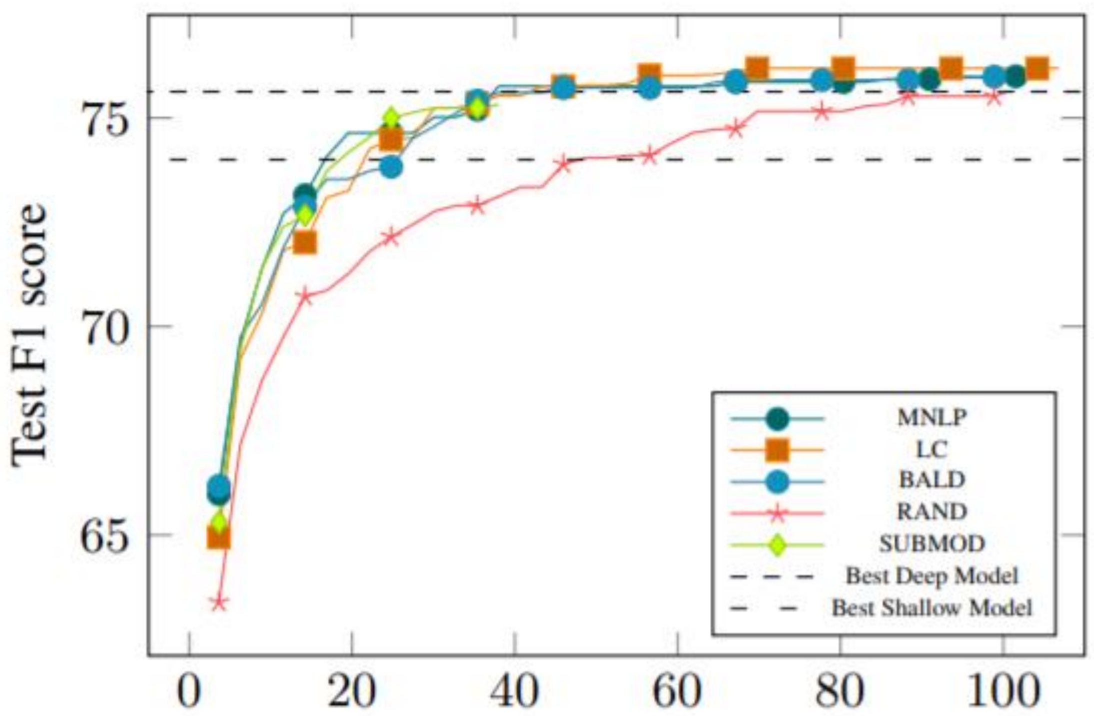
Shen et al., 2018 (ICLR-2018) (2)



(a) OntoNotes-5.0 English



(b) OntoNotes-5.0 Chinese

- → Deep models outperform shallow
- → AL **achieves 99%** performance of the best deep model trained on full data **using only 24.9%** of data on the English dataset and 30.1% on Chinese dataset

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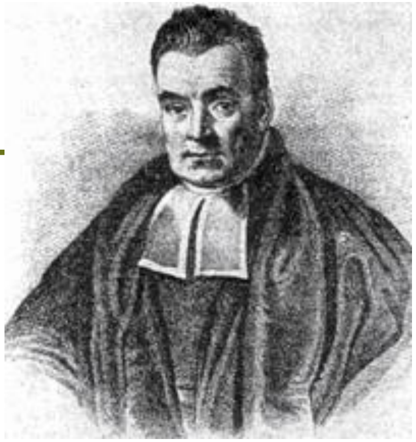
Siddhant and Lipton, 2018 (EMNLP-2018) (1)



“Deep Bayesian Active Learning for Natural Language Processing: Results of a Large-Scale Empirical Study” (Siddhant and Lipton, 2018)

→ Monte Carlo dropout (Gal et al., 2017)

- We can make several varying predictions using dropout on inference
- Quality of estimates:

“least confident” < **“Monet Carlo dropout QbC”** < “QbC on ensemble”

→ Deep Bayesian active learning (Bayes by backprop)

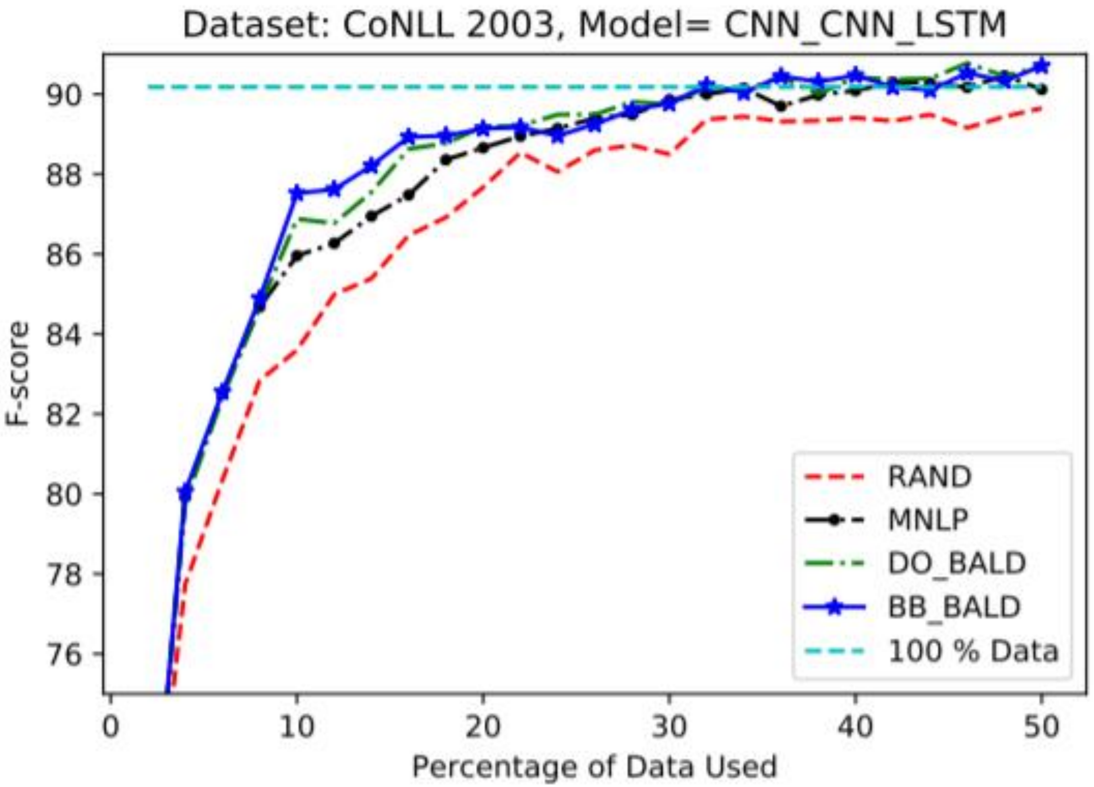
- Use Bayesian NN that maintains a probability distribution over model parameters
- Perform variational inference to obtain posterior, use MC to get uncertainty estimates

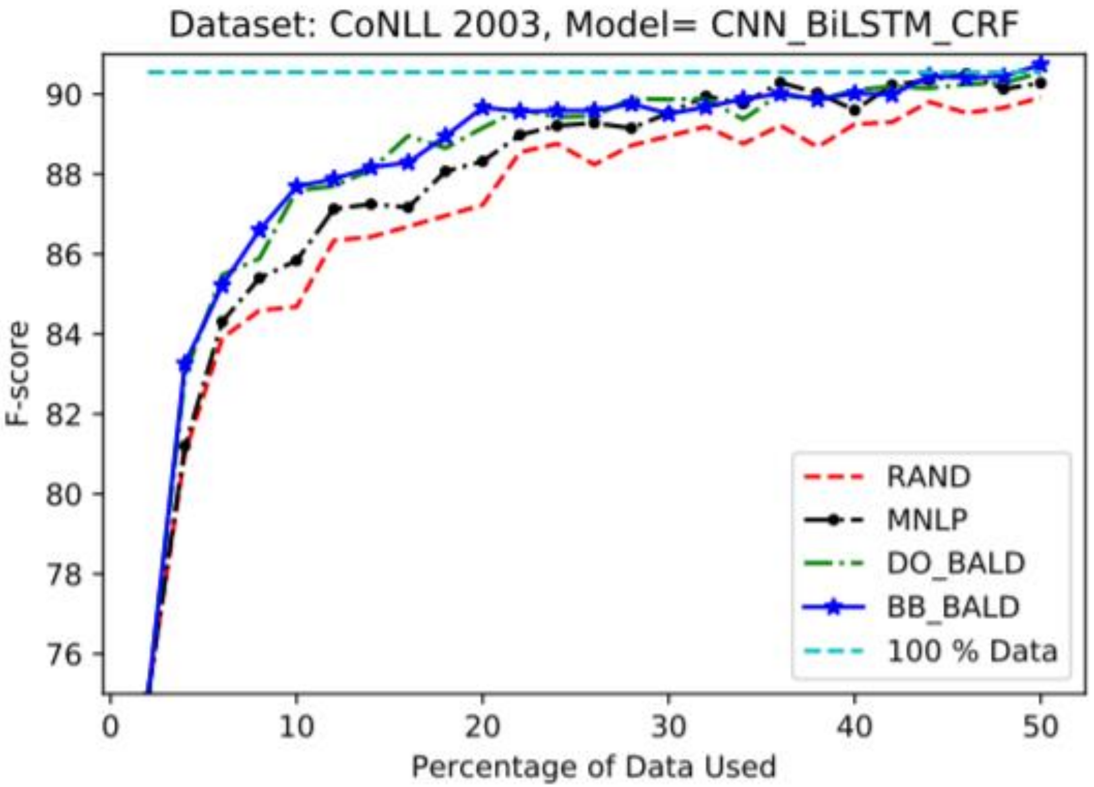
Siddhant and Lipton, 2018 (EMNLP-2018) (2)

- → Bayesian AL by disagreement (BALD):

$$f_i = 1 - \frac{\max_y \left|\{m : \mathrm{argmax}_{y'} \mathbb{P}^m[y_i = y'] = y\}\right|}{M}$$

- → Architectures: CNN-CNN-LSTM, CNN-BiLSTM-CRF
- → Experiments on CoNLL-2003, OntoNotes 5.0, and datasets for SRL and sentence classification





Bayesian > Least Confidence

Erdmann et al., 2019 (NAACL-2019)

<u>Practical, Efficient, and Customizable Active Learning for Named Entity Recognition in the Digital Humanities (Erdmann et al., 2019)</u>

→ Novel Pre-Tag DeLex algorithm

- → Gazetteers to bootstrap annotation and to detect novel objects
- → 3 delexicalized models trained on subsets manually labeled data and automatically labeled data. => Bootstrapping cycle:

1. Use extracted objects to label data and <u>detect novel contexts</u> for objects
2. Learn contexts and use them to <u>detect novel objects</u>
3. Use extracted objects to label data and <u>detect novel contexts</u> for objects
4. …

→ Compared to: MNLP

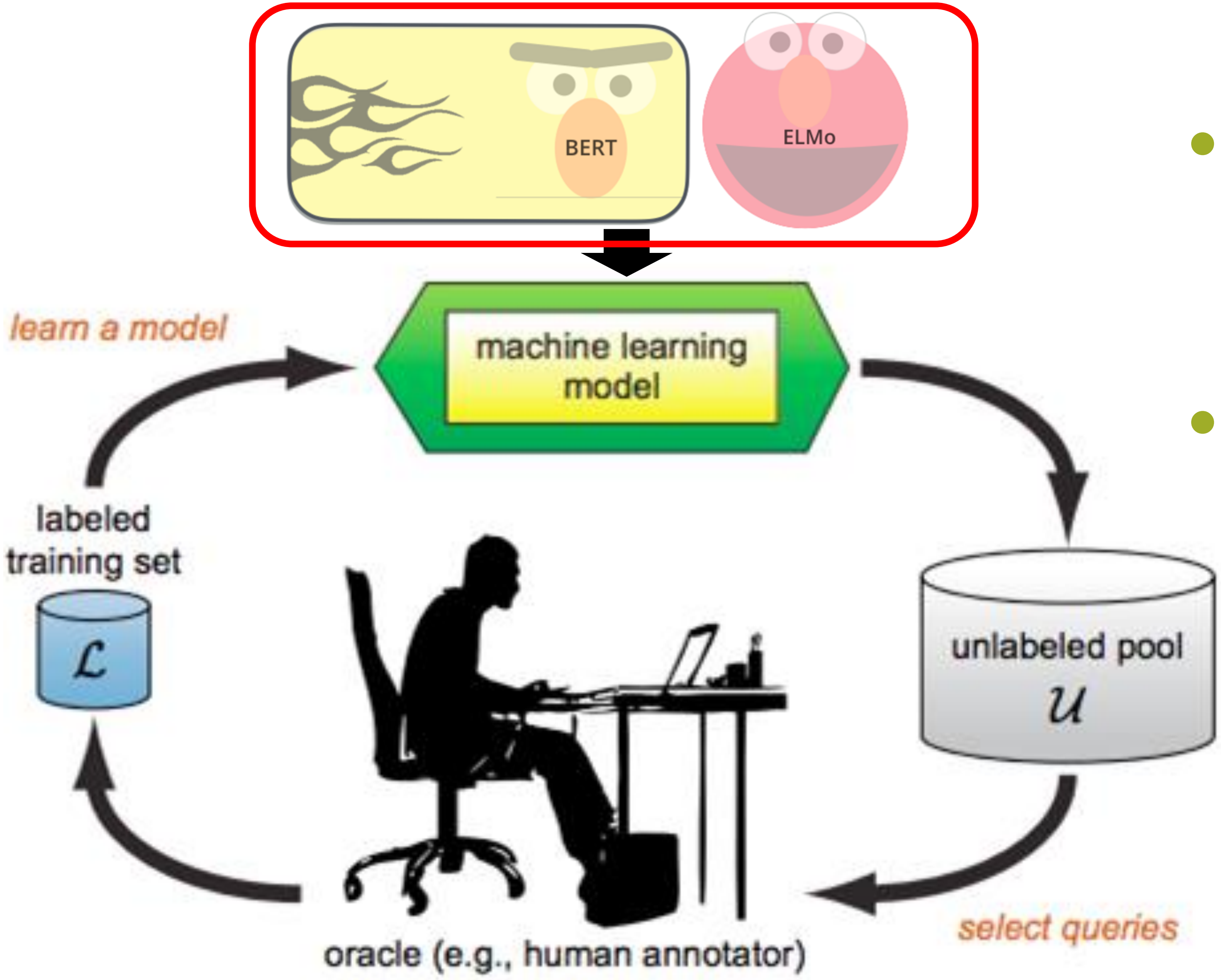
→ Architectures: BiLSTM-CRF, CNN-BiLSTM, and pure CRF

→ Experiments on Spanish CoNLL, GermEval, Arabic and Latin corpora

Active Learning with Deep Pre-trained Models for Sequence Tagging of Clinical and Biomedical Texts (IEEE BIBM 2019)

Artem Shelmanov, Vadim Liventsev, Danil Kireev, Nikita Khromov, Alexander Panchenko, Dmitry Dylov

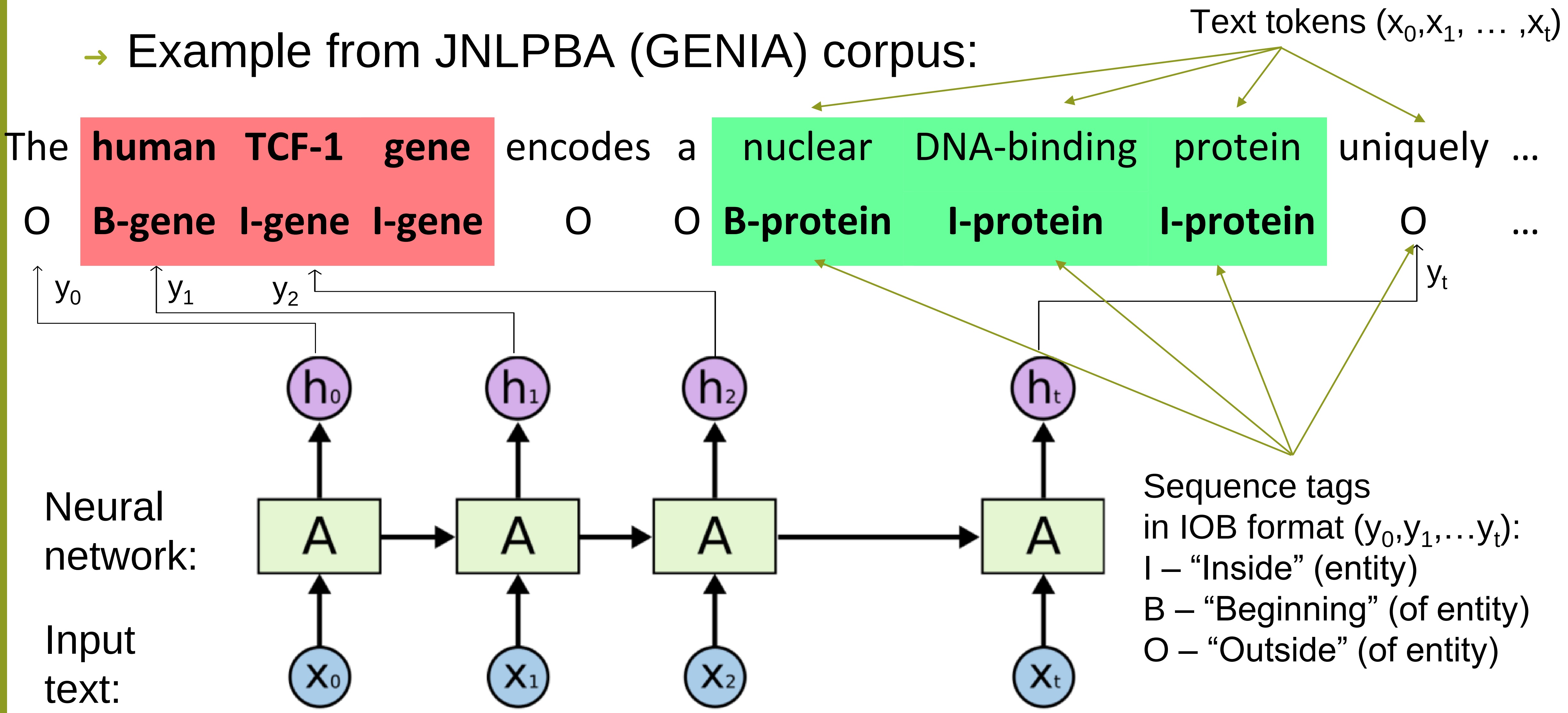
Basic Idea



- AL for IE with transfer learning:
  - → Deep pre-trained models BERT, ELMo, etc.
- Transfer learning:
  - → Provides universal feature set
  - → Enables neural network training on small datasets
  - → Very powerful for streamline NLP tasks

Sequence Tagging Task (NER)

→ Example from JNLPBA (GENIA) corpus:



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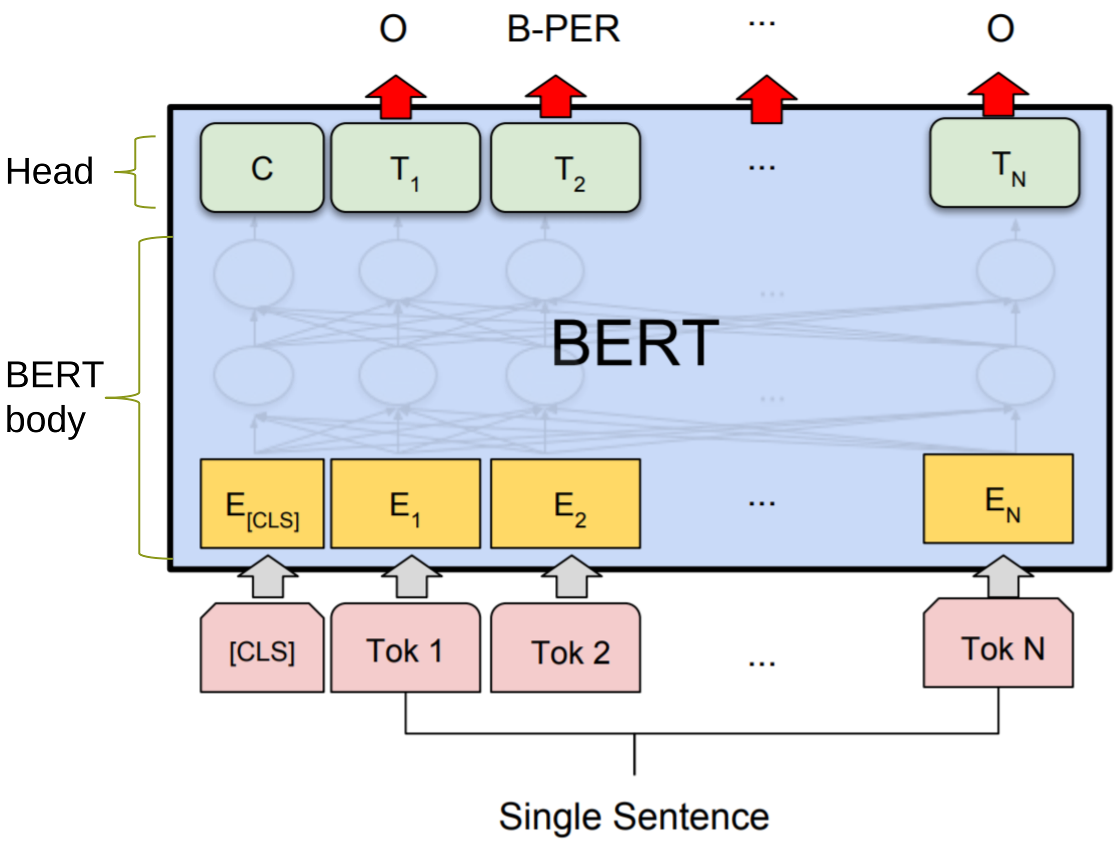
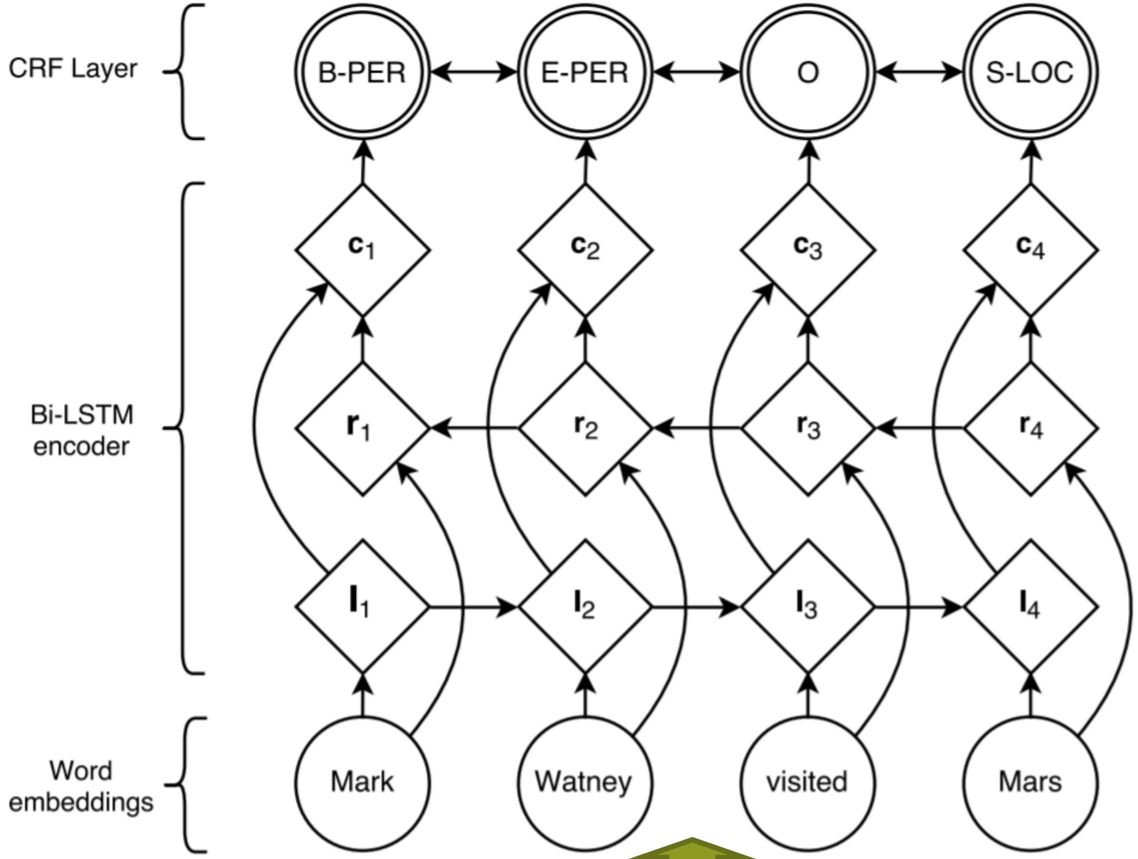
NN Architectures

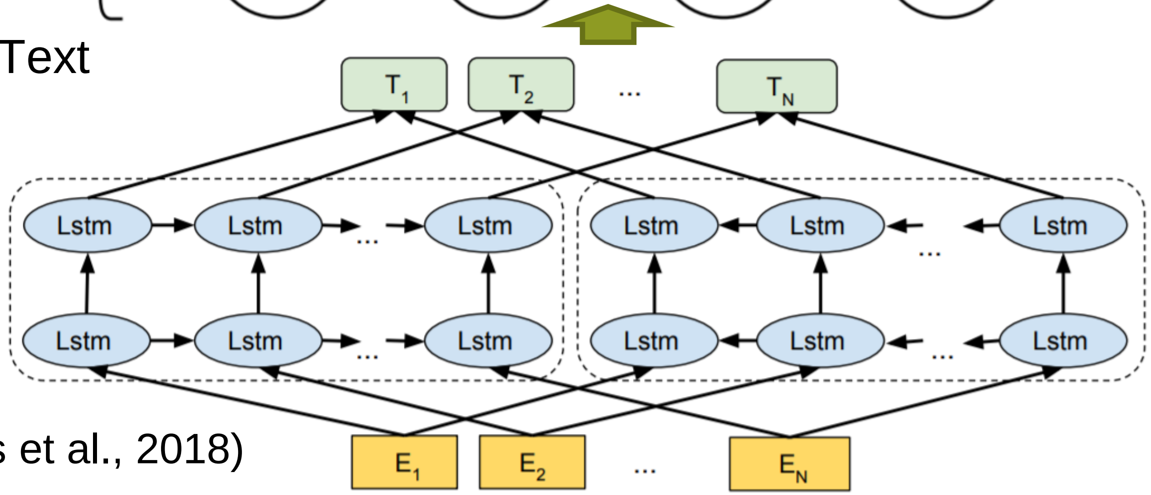


BERT (Devlin et al., 2019)

BiLSTM-CRF (Ma and Hovy, 2016)



fastText



ELMo (Peters et al., 2018)

Query Strategies

- MNLP:

Unannotated objects are sorted in ascending order by the average log probability of sequence tags

$$\mathrm{MNLP} = \max_{\{y_j\}} \frac{1}{n} \sum_{i}^{n} \log P(y_i | \{y_j\} \setminus y_i, \{x_j\})$$

- Modification MNLP-mod:

$$\text{MNLP-mod} = \text{MNLP} \cdot \alpha, \ \text{where}$$

$$\alpha = \begin{cases} \frac{1}{\gamma} & \text{if y contains a tag `B-<type>'} \\ 1 & \text{otherwise} \end{cases}$$

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Corpora for Experiments

- I2B2 Heart risk factors (Stubbs et al., 2014)
  - We generated three datasets with entity-level annotations using the original data with document-level annotations

	Hypertension	**CAD**	**Diabetes**
Train, # sent.	9,871	25,924	14,183
Test, # sent.	6,813	16,560	8,088
% with entities	13.0	3.5	7.3

- JNLPBA /Genia (Collier et al., 2004)
  - 18,546 sentences for training and 3,856 for testing
  - 5 types of entities: “DNA”, “protein”, “cell type”, and “cell line”

BERT Finetuning Details

- You cannot finetune BERT like (Devlin, et al 2019) on very small data
- They use learning rate scheduler: warm-up over the first steps, and linear decay of the learning rate
- With very small data such scheduler is detrimental

We used:

- Early stopping with number of tolerance epochs of 4, max number of epochs: 20 (however, in most cases BERT stops training earlier)
- Adam, learning rate: 5e-5 (*10 for the head), 0.01 L2 weight decay, batch size 45, gradient clipping: 1.0
- No learning rate annealing

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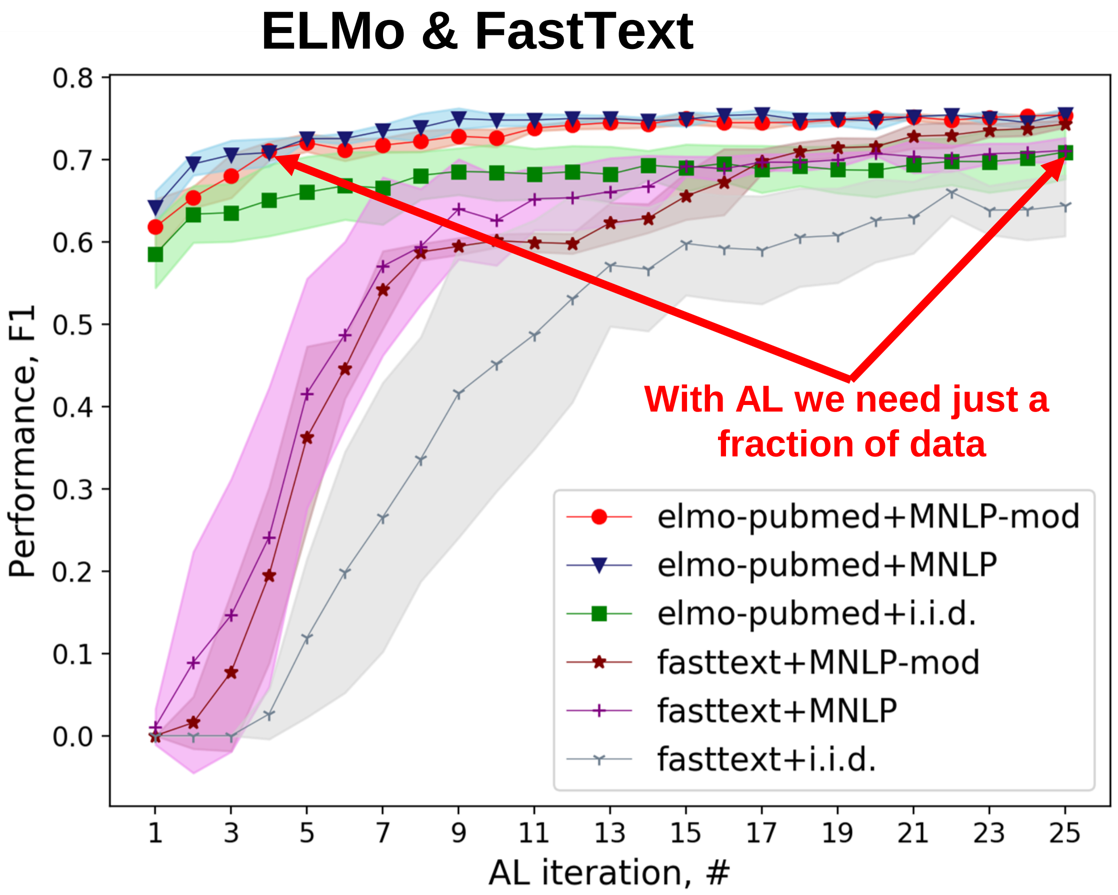
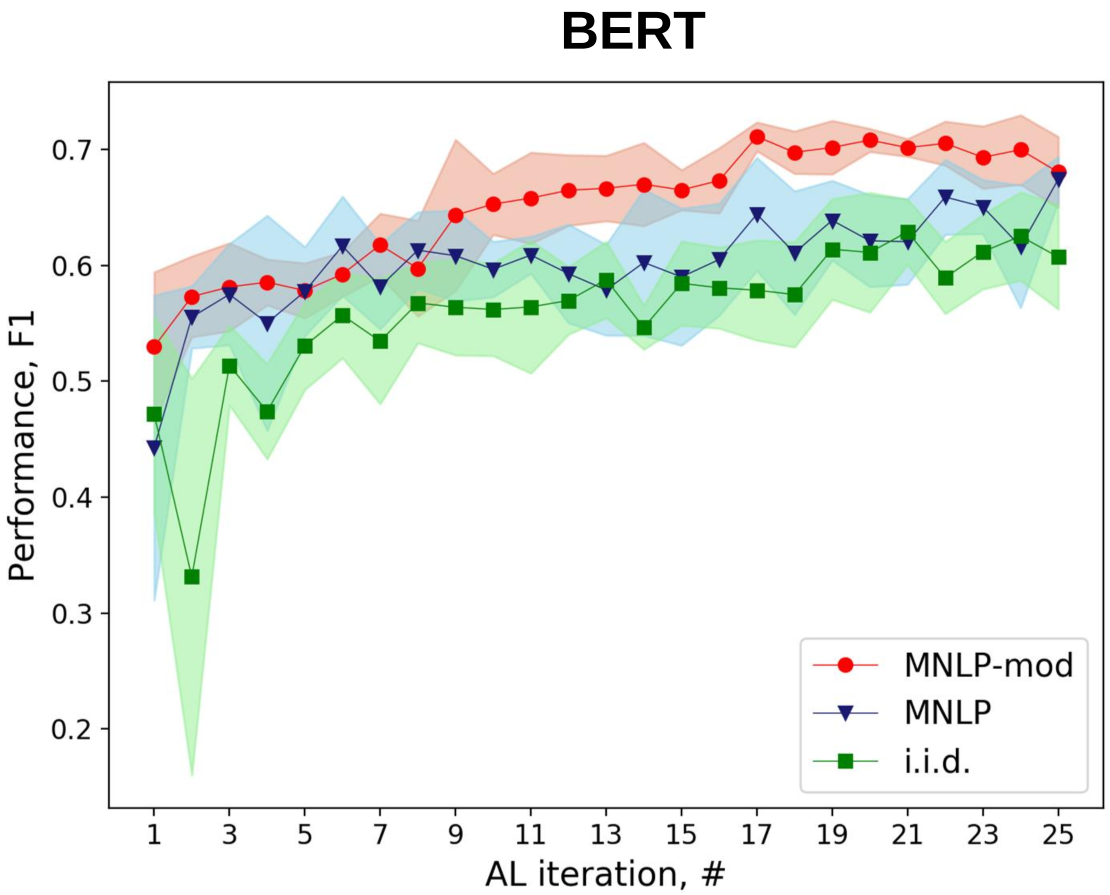
Results on i2b2 Heart Risk Factors (Diabetes)





- Active learning is better than i.i.d. sampling on every dataset and with every model
- Sequence taggers based on deep pre-trained models can be trained on very small data compared to the model based on shallow DSM (fastText)

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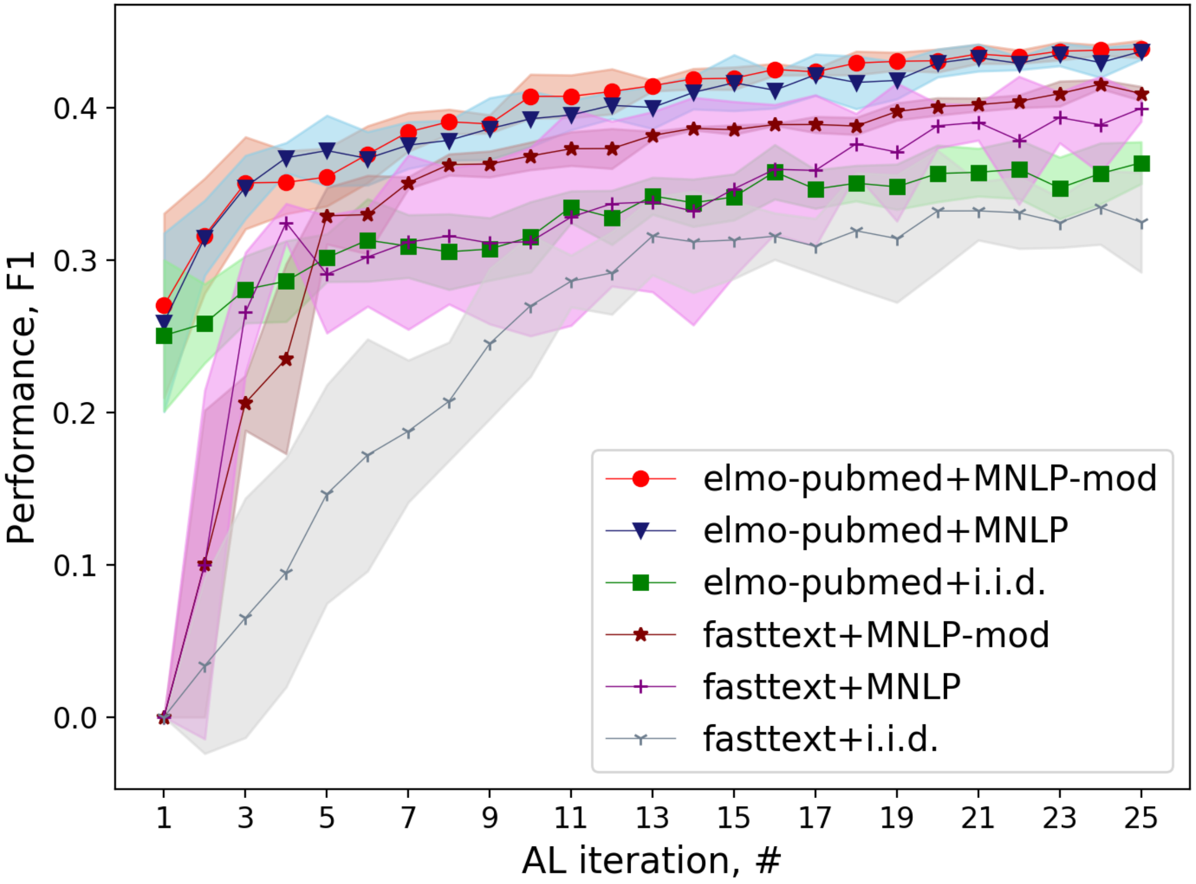
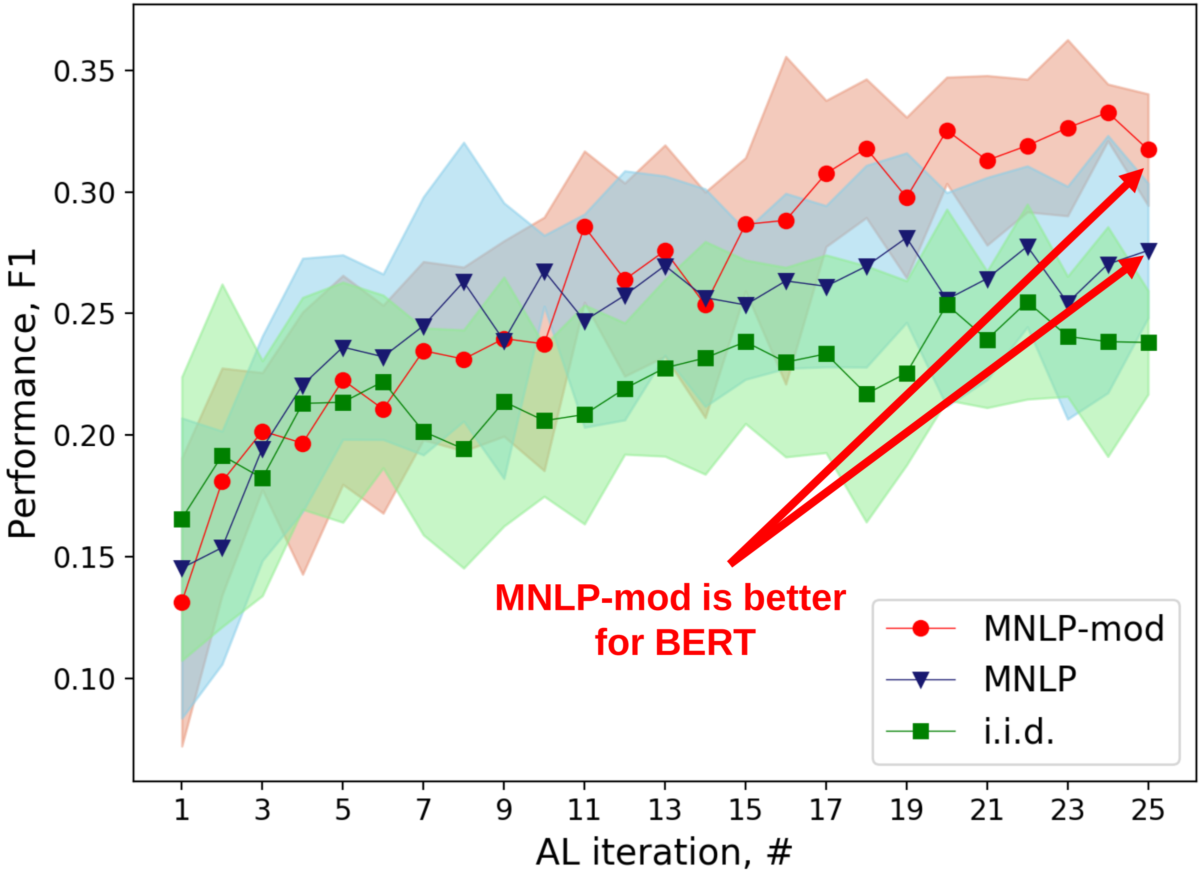
Results on i2b2 Heart Risk Factors (CAD)

ELMo & FastText



BERT



- MNLP-mod potentially helps to deal with very skewed datasets

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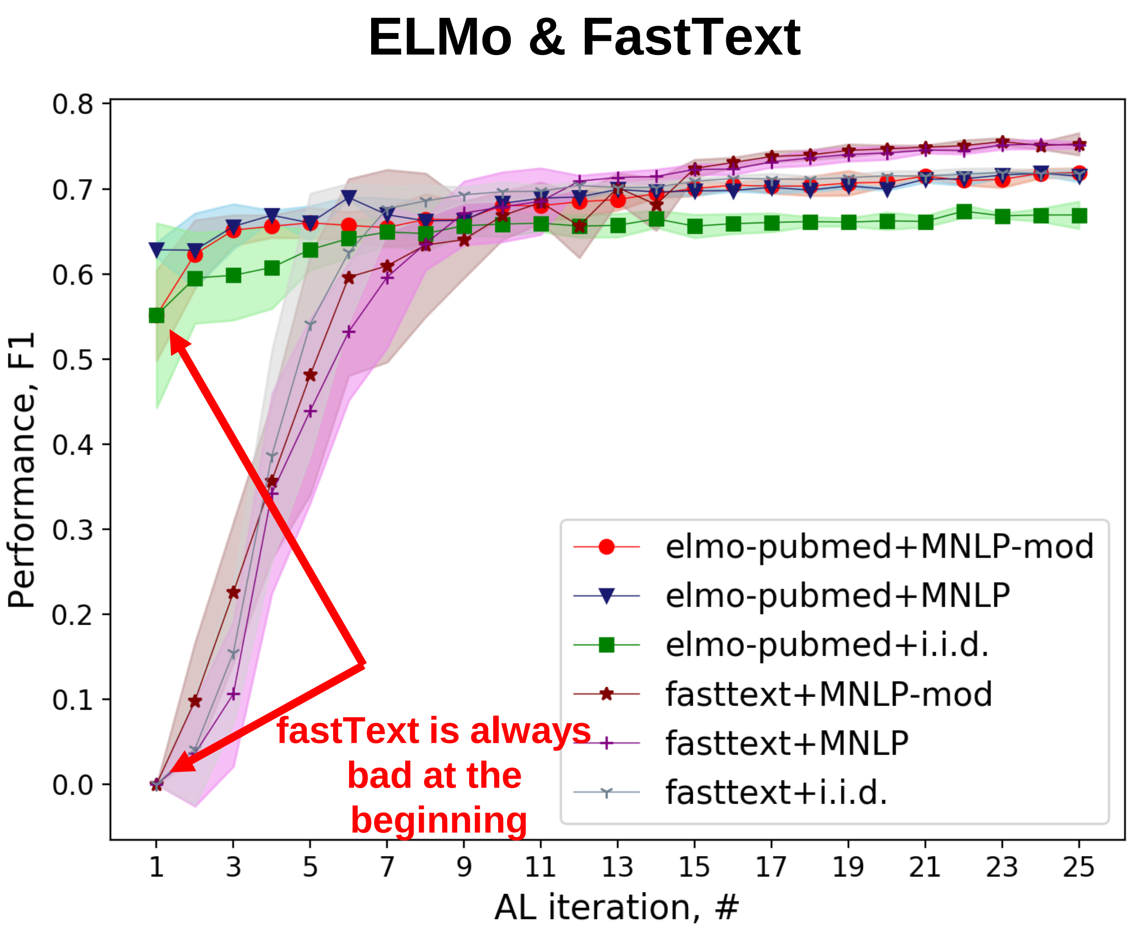
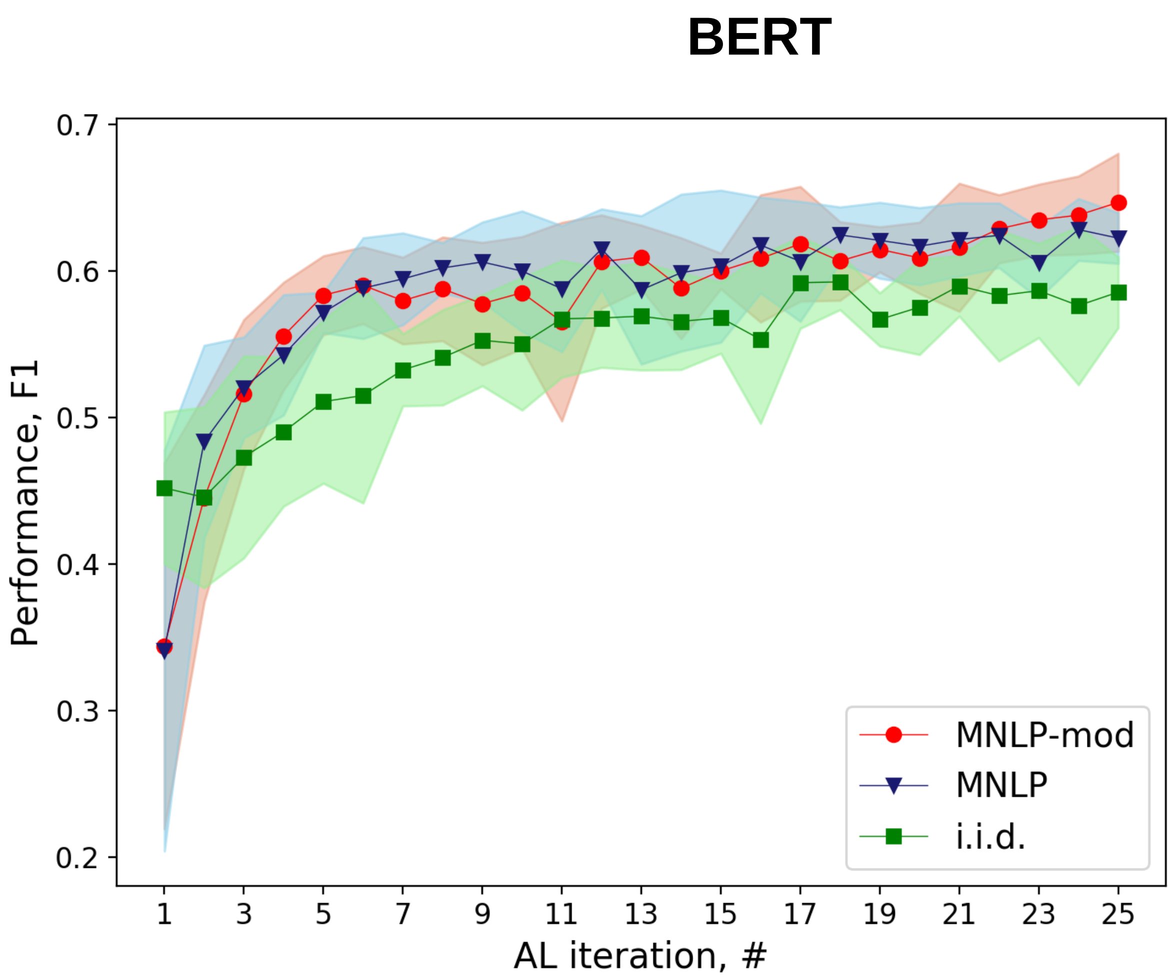
Results on i2b2 Heart Risk Factors (Hypertension)





- In this experiment, fastText outperforms deep pre-trained models, although it still worse in the beginning

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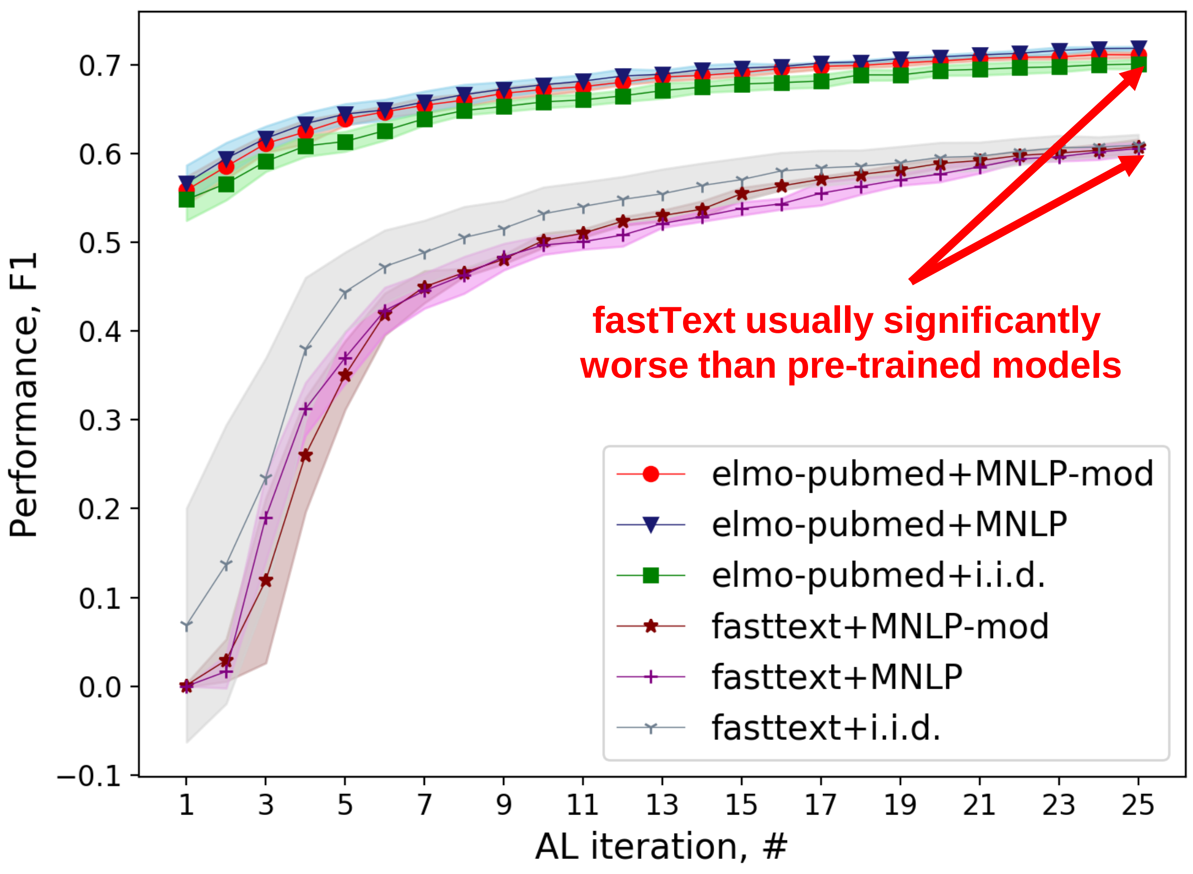
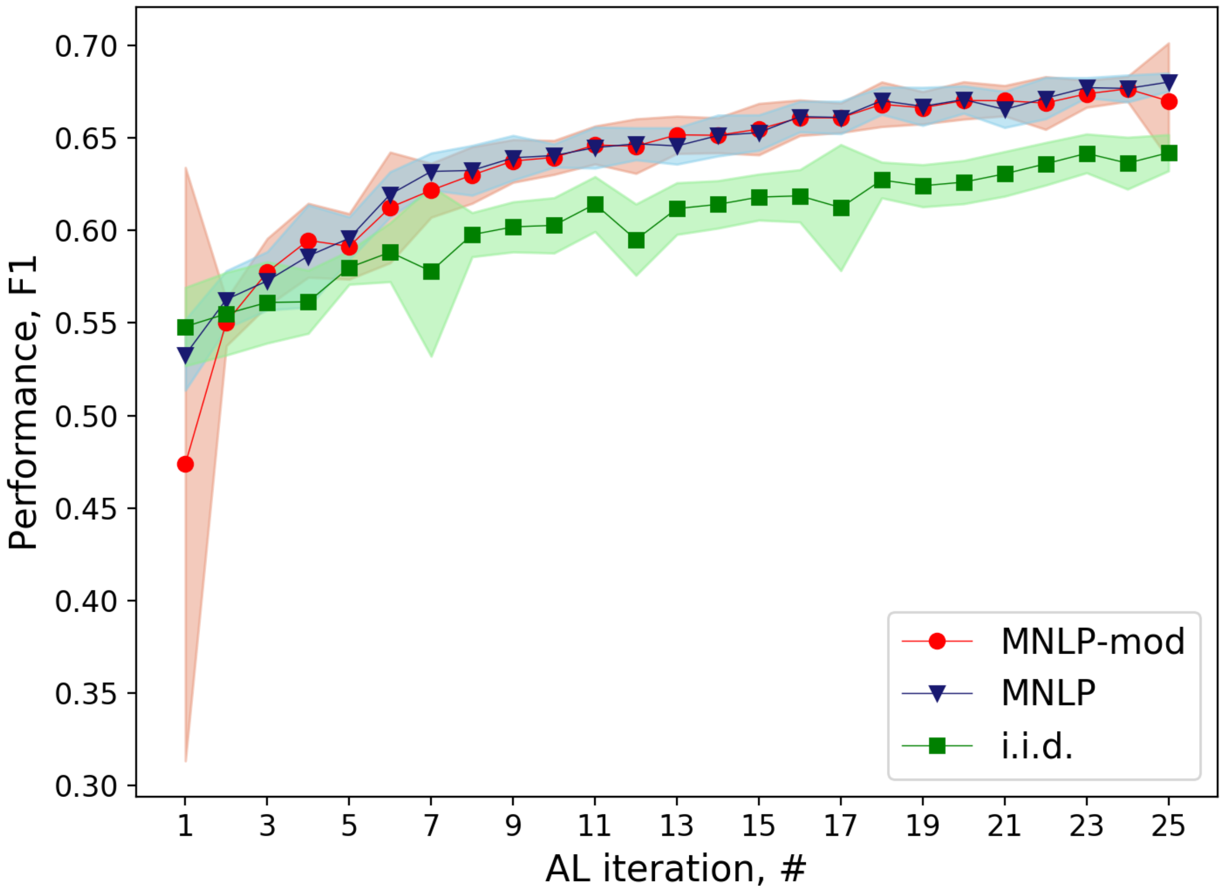
Results on JNLPBA

ELMo & FastText



BERT



- Deep pre-trained models overall perform better than fastText (except hypertension dataset)

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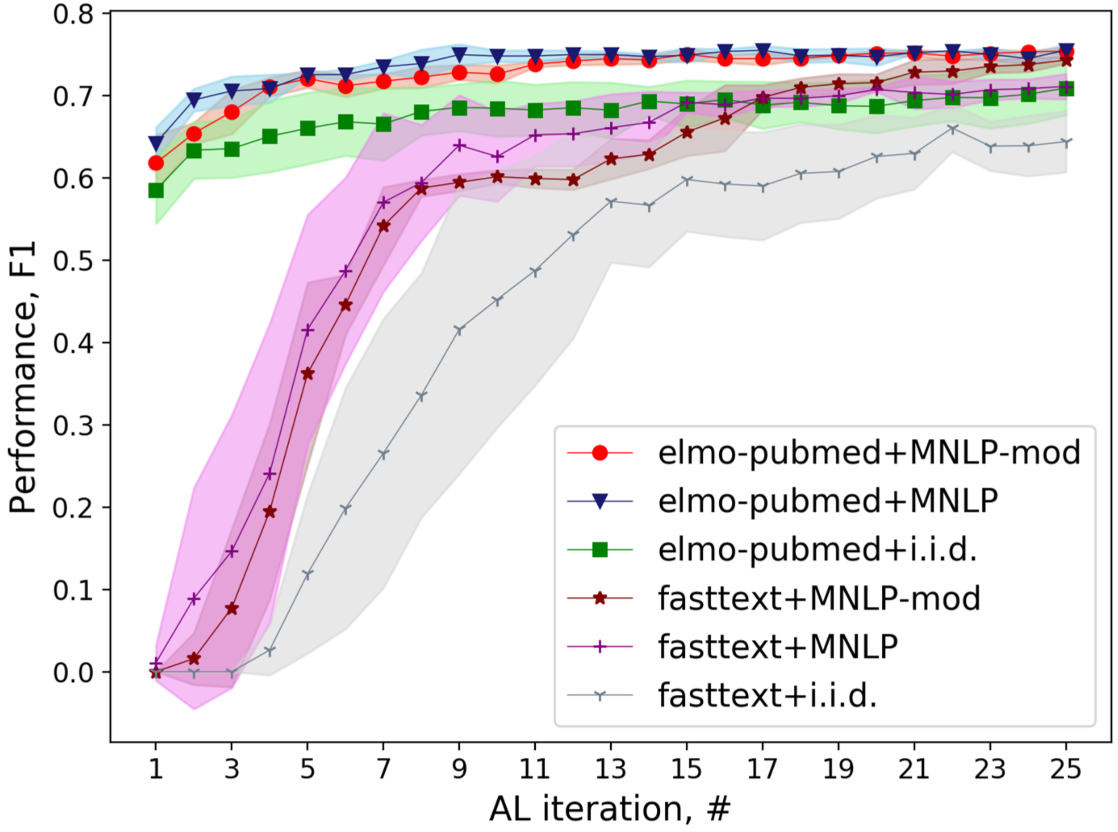
Summary

- Active learning is better than i.i.d. sampling on every dataset and with every model
- Sequence taggers based on deep pre-trained models can be trained on very small data compared to the model based on shallow DSM
- Deep pre-trained models overall perform better than fastText (except hypertension dataset)
- ELMo has the best performance overall, but BERT is several times faster, so it is still practical to favor BERT in AL

ELMo & FastText



i2b2: Diabetes

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AL for Biomedical Research in Cardiology

In conjunction with
National Cardiological Center

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We use AL for Biomedical Research in Cardiology

Ишемическая болезнь сердца Артериальная гипертония

Хроническая сердечная недостаточность Сахарный диабет

Фибрилляция предсердий

Диагноз заключительный ИБС: Инфаркт миокарда без подъема сегмента ST от 05.01.18г. Ранняя постинфарктная стенокардия. Транслюминальная балонная ангиопластика коронарных артерий со стентированием ствола левой коронарной артерии с переходом на проксимальный и средний сегмент передней нисходящей артерии стентами Promus Element 4,0x32мм и Promus Element 3,5x38мм., проксимальной трети от устья огибающей артерии Promus Element 3,5x12 мм. от 18.01.18г. Атеросклероз коронарных артерий (окклюзия ПКА, субтотальный стеноз ствола ЛКА, 90% стеноз устья ОА). Постинфарктный кардиосклероз (инфаркт миокарда от 2004г).Нарушение ритма сердца: впервые возникший пароксизм фибрилляции предсердий, тахиформа от 15.01.18г. Впервые возникший пароксизм трепетания предсердий от 18.01.18г. Хроническая сердечная недостаточность 2ФК по NYHA. Артериальная гипертензия 3 ст, риск 4. Сахарный диабет 2 типа. Диабетическая микромакроангиопатия. Диабетическая дистальная полинейропатия, сенсорно-моторная форма.Синдром диабетической стопы, нейроишемическая форма.Облитерирующий атеросклероз нижних конечностей. Балонная ангиопластика и стентирование левой ПБА от 19.05.11г.

Ischemic stroke risk assessment:

CHA2DS2-VASc:

4 пунктов

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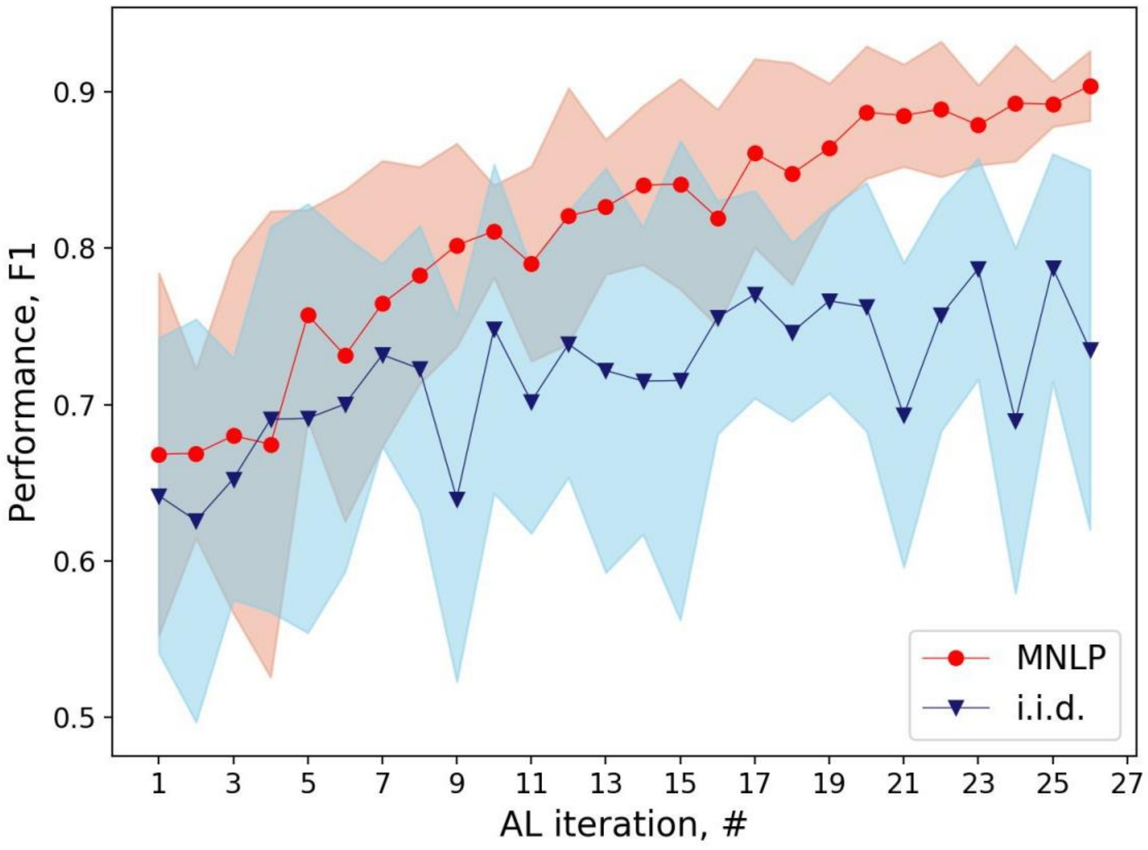
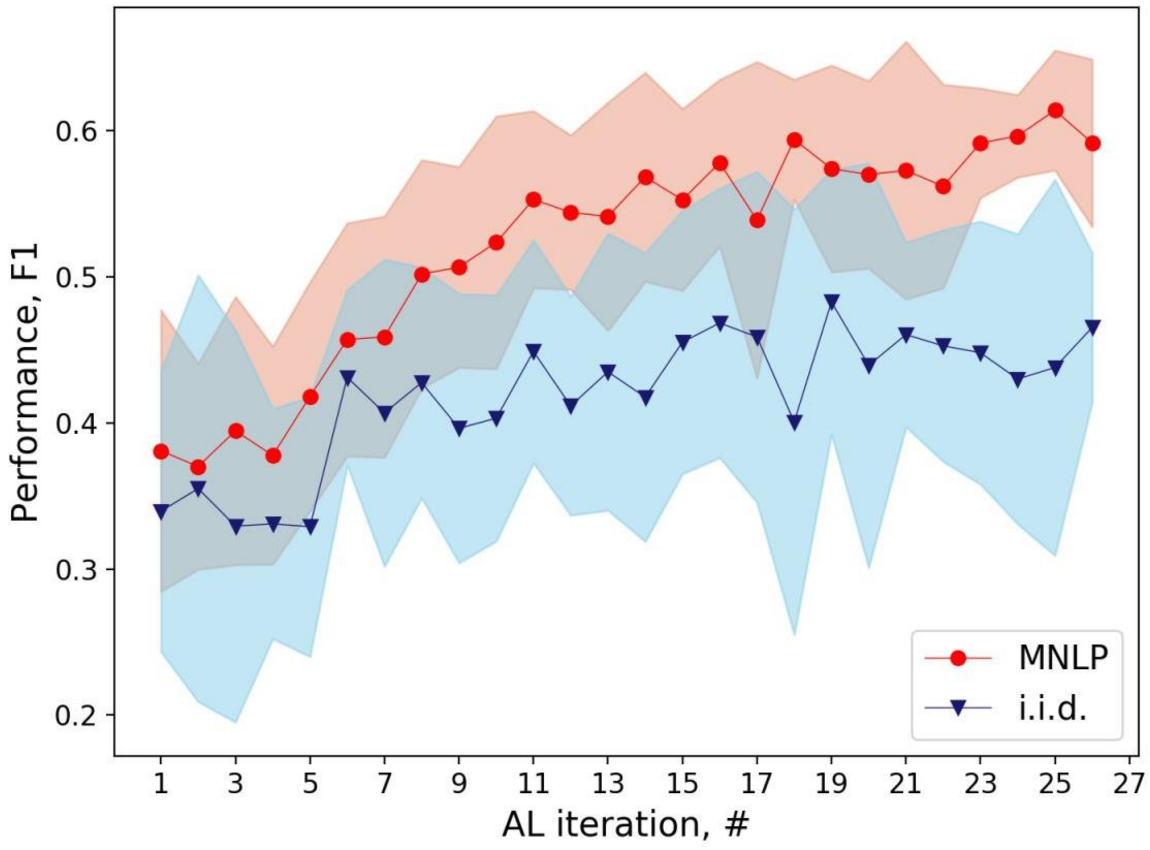
Results on Russian-language Data from National Cardiological Center (1)

Hypertension



Peripheral Arterial Disease



BERT for token classification (based on RuBERT)

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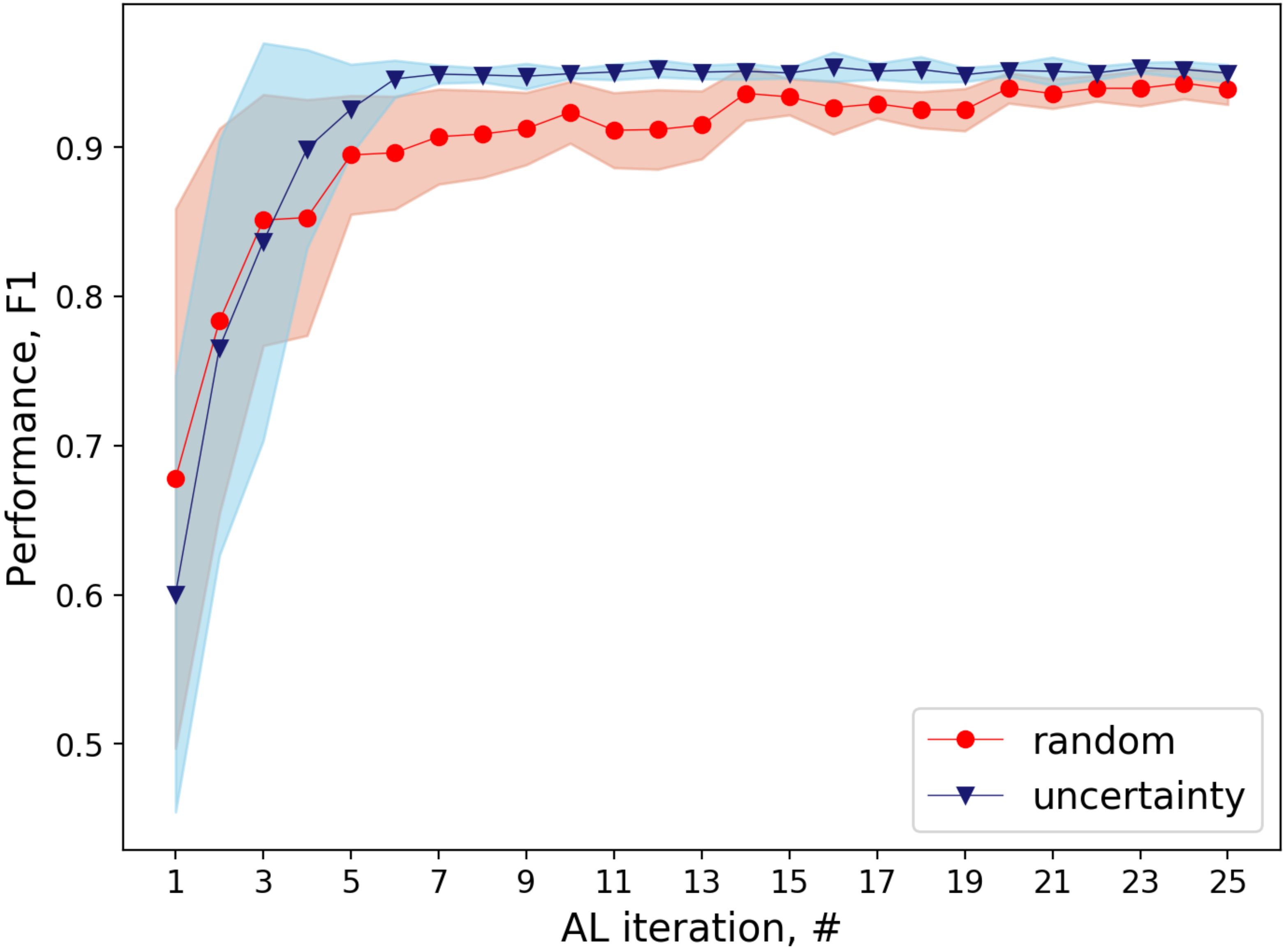
Results on Russian-language Data from National Cardiological Center (2)



- Hypertension
- ELMo + BiLSTM-CRF
- ELMo for Russian from RusVectores

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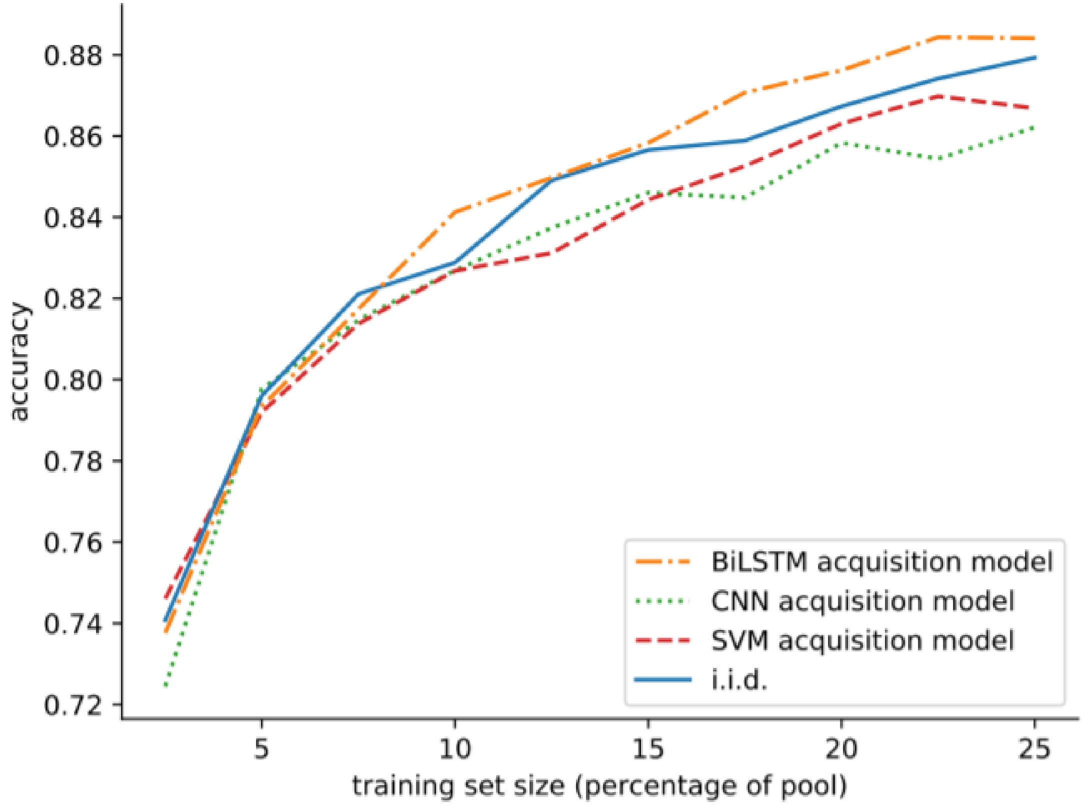
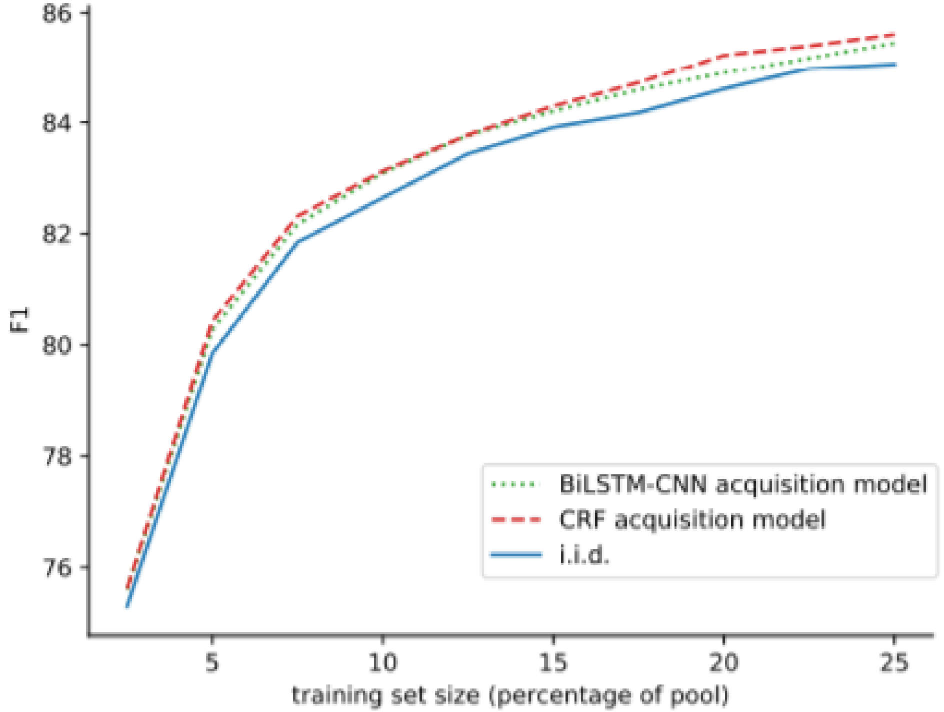
Disclaimer: AL sometimes does not work!

EMNLP 2019: "Practical obstacles to deploying active learning" (Lowell et al., 2019)

→ If you use one model to create a dataset with AL and train another model on the result dataset you can get a performance drop!



BiLSTM performance on text classification
Subjectivity corpus (Pang and Lee, 2004)



BiLSTM-CNN on
OntoNotes 5.0

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Key Takeaways

- **Do not write hand-crafted rules! Instead, annotate quickly!**
- **Deep pre-trained models and active learning is a powerful combination**

- Active learning is especially good when you cannot do crowdsourcing (e.g., in clinical medicine or biomedicine)
- BERT training procedure on very small data is different from the method presented in the original paper (Devlin et al., 2019)
- BERT performed worse in the AL setting (in our experiments) than ELMo-BiLSTM-CRF. However, it is computationally faster
- AL is biased sampling a priory! You cannot test on such data
- AL sometimes does not work! Especially when you use different models for acquisition and evaluation

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