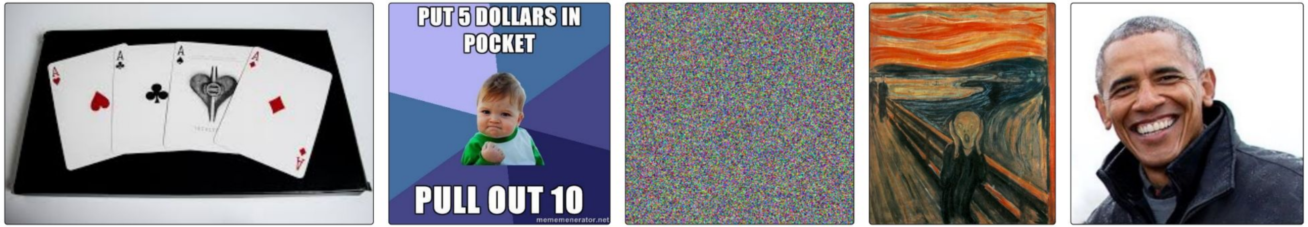
Out-of-distribution detection for neural NLP models

Hrant Khachatrian @ YerevaNN

Joint work with Karen Hambardzumyan

#AMLD2019

Motivation: image classification



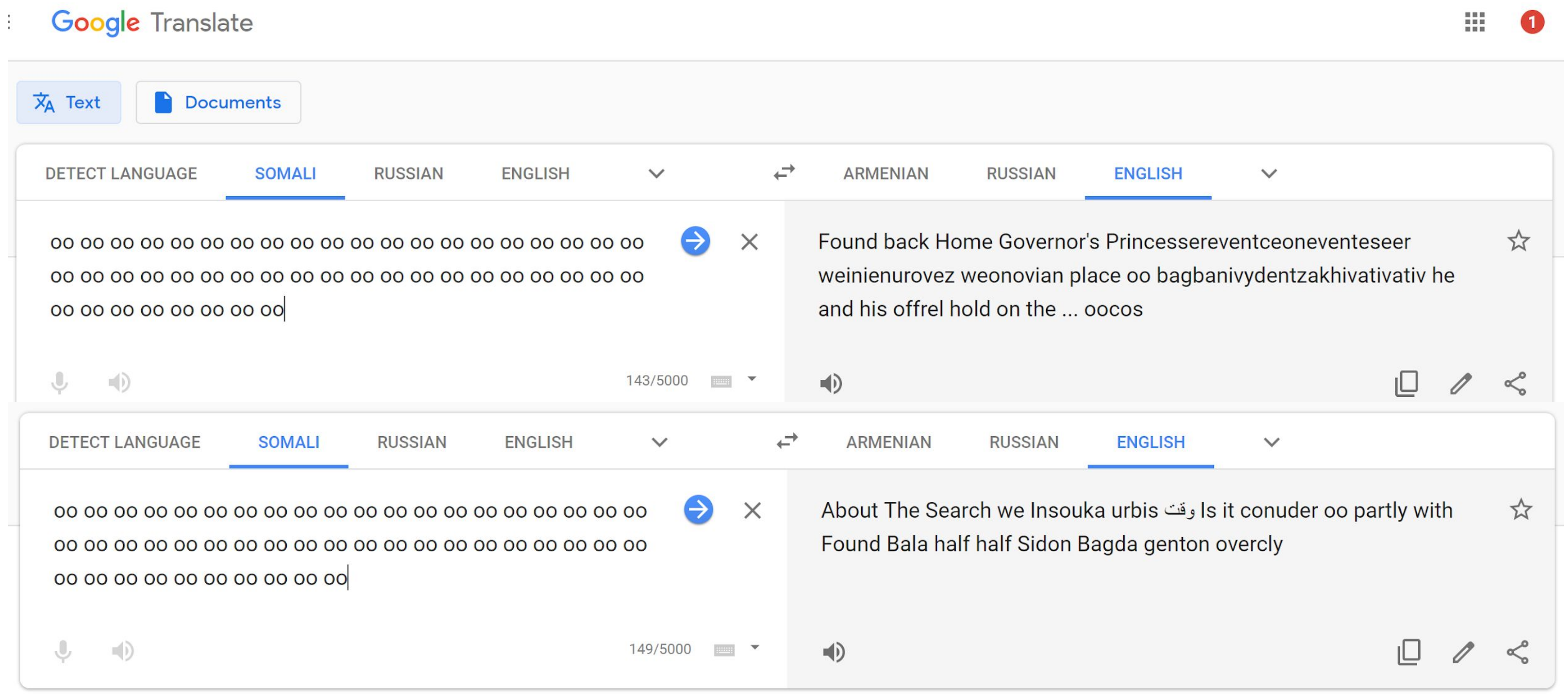
DenseNet 161 (2017)	Envelope 31%	Balance Beam 52%	Chainlink Fence 31%	Chest 37%	Tench 36%
SqueezeNet (2016)	Binder 43%	Balance Beam 18%	Poncho 32%	Jean 30%	Suit 21%
ResNet 152 (2015)	Envelope 40%	Pacifier 33%	Chain Mail 29%	Dust Cover 52%	Sweatshirt 25%
VGG 19 (2014)	Binder 51%	Dust Cover 44%	Window Screen 5%	Chest 11%	Sweatshirt 46%
AlexNet (2012)	T-shirt 16%	Dust Cover 22%	Cardigan 12%	Theater Curtain 3%	Coho 37%

Figure 1: The arbitrary predictions of several popular networks [2, 3, 4, 5, 6] that are trained on ImageNet [1] on unseen data. The red predictions are entirely wrong, the green predictions are justifiable, the orange predictions are less justifiable. The middle image is noise sampled from $\mathcal{N}(\mu = 0.5, \sigma = 0.25)$ without any modifications. This unpredictable behaviour is not limited to demonstrated architectures. We show that merely thresholding the output probability is not a reliable method to detect these problematic instances.

Figure taken from [Shafaei et al., 2018]

Alireza Shafaei, Mark Schmidt, and James J. Little, *Does Your Model Know the Digit 6 Is Not a Cat? A Less Biased Evaluation of "Outlier" Detectors*

Motivation: machine translation



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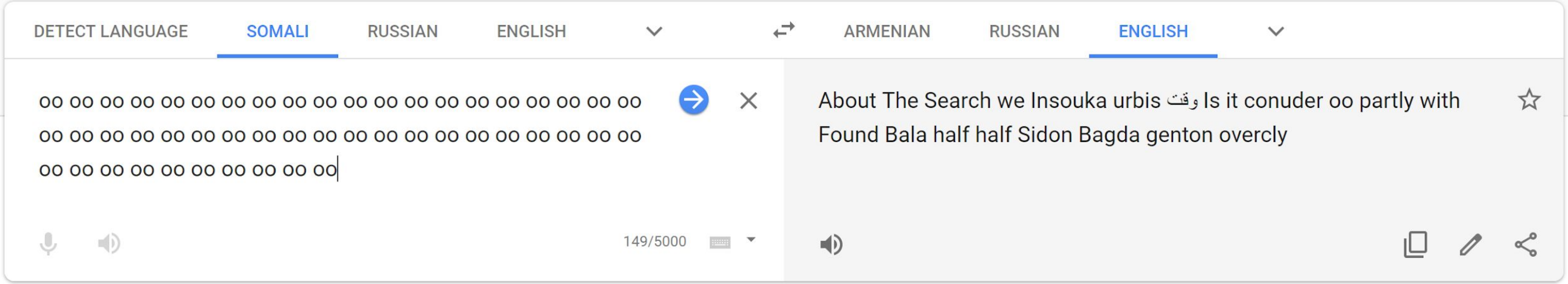
The problem

- Can we look at the input sample and the output of the neural network and figure out whether we should trust the output?
  - Intuitively, “oo oo oo ….” is very far from the all the sentences used in the training process. Therefore, we should not expect reasonable output from the network.
  - Can we “quantify” this?



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Basic approach

- [Hendrycks and Gimpel, ICLR 2017] proposed a simple baseline
- *“Correctly classified examples tend to have greater **maximum softmax probabilities** than erroneously classified and out-of-distribution examples, allowing for their detection”*
- Let f(x) be the output of the last layer of the neural network (before softmax)

$$score_{base} = \max softmax(f(x))$$

- Use this score to discriminate correctly and incorrectly classified examples:

  AUC = 0.93 for CIFAR-10 test set

  AUC = 0.87 for CIFAR-100 test set

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- Use this score to discriminate CIFAR-10 and LSUN test set samples:

  AUC = 0.95 for DenseNet-101

Better approach: ODIN

- [Liang et al., ICLR 2018] proposed an improvement
- ODIN algorithm adds two tricks:
  - Use adversarial-like perturbation
  - Use high temperature softmax

$$\hat{x} = x + \epsilon \operatorname{sgn}(\nabla_x f_{\hat{y}}(x))$$

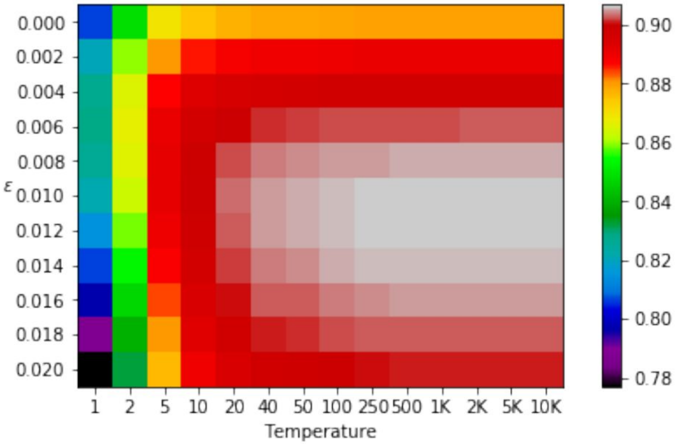
$$score_{\text{ODIN}} = \max softmax_T\left(f\left(\hat{x}\right)\right)$$

- Use this score to discriminate CIFAR-10 and LSUN test set samples:

  AUC = 0.98 for DenseNet-101 (vs 0.95 of the baseline)

Do these techniques work for NLP tasks?

- Sentiment analysis
  - A simple bi-LSTM trained on Yelp Reviews dataset
  - Discriminate sentences from Yelp Reviews and Stanford Sentiment Treebank
  - AUC = 0.907



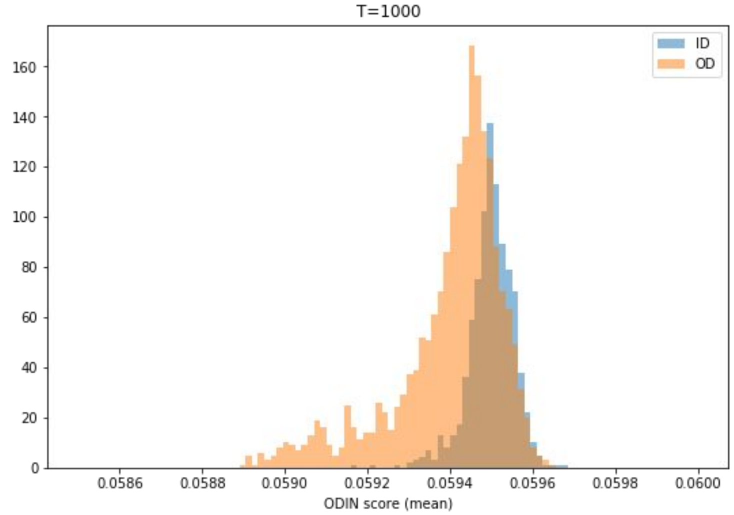
There is an optimal value for ε

AUC

High temperatures are better

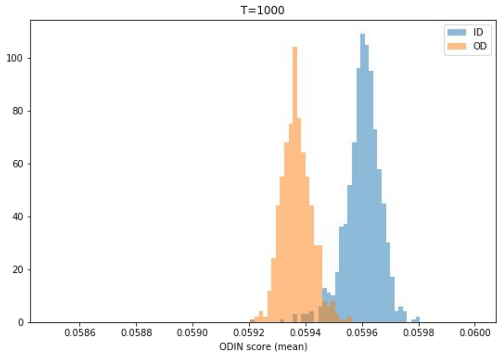
Do these techniques work for NLP tasks?

- Part-of-speech tagging
  - We train on UD English-LinES
  - We test on two datasets:
    - **UD English-EWT: AUC=0.751**
      - Probably because EWT has a subset very similar to LinES

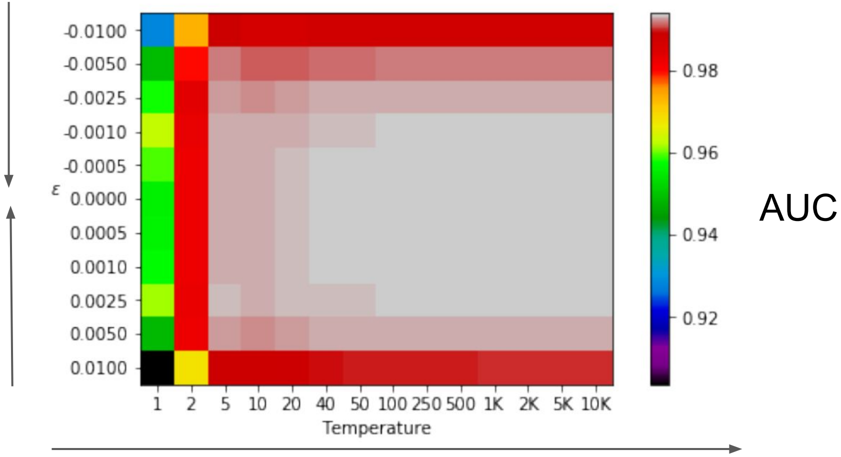


Do these techniques work for NLP tasks?

- Part-of-speech tagging
  - We train on UD English-LinES
  - We test on two datasets:
    - UD English-EWT: AUC=0.751
      - Probably because EWT has a subset very similar to LinES
    - **UD Dutch-Alpino: AUC=0.991**
      - ε>0 doesn’t help!



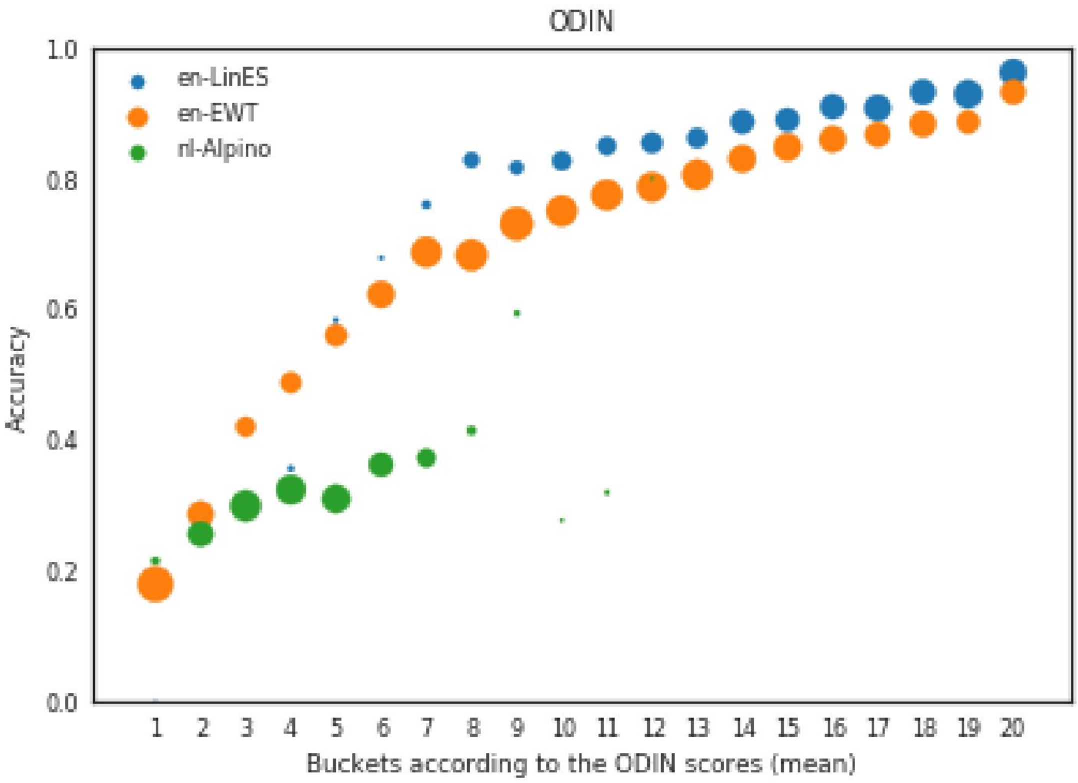
ε=0 is the best one



High temperatures are still better

What does it mean for practice?

- Train on English LinES
- Combine the samples from the test sets of 3 datasets
- Order the samples by ODIN score and split them into 20 buckets
- Calculate POS tagging accuracy for each (bucket, dataset) pair



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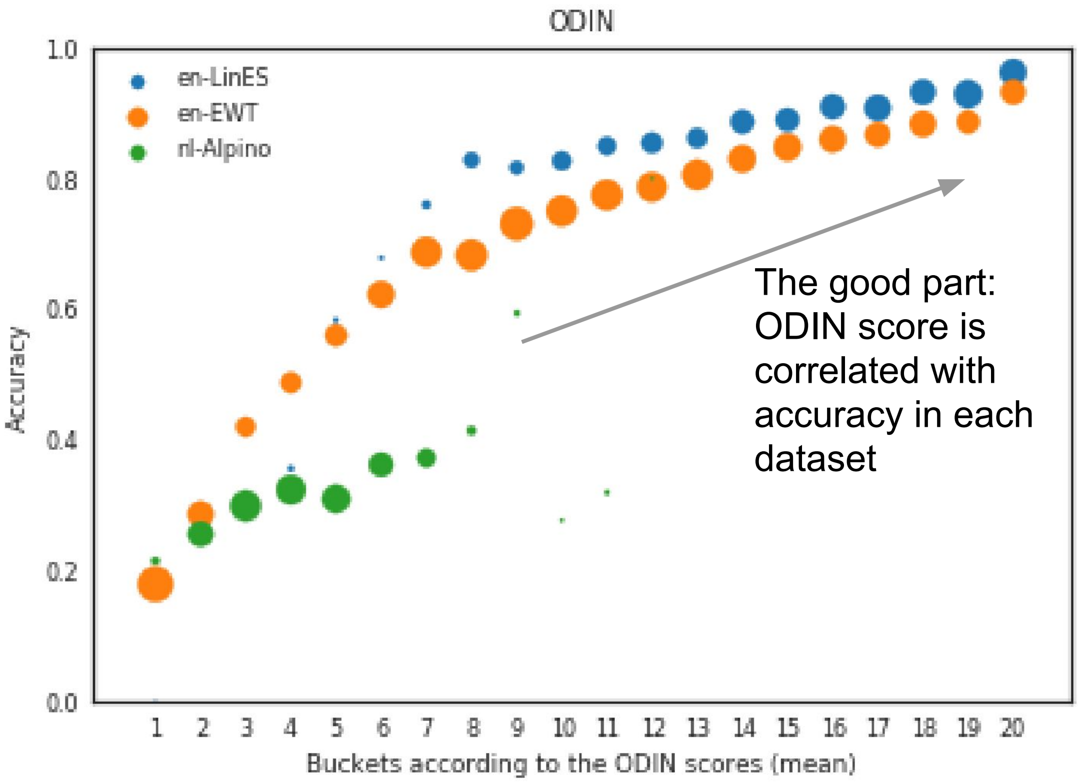

The good part: ODIN score is correlated with accuracy in each dataset

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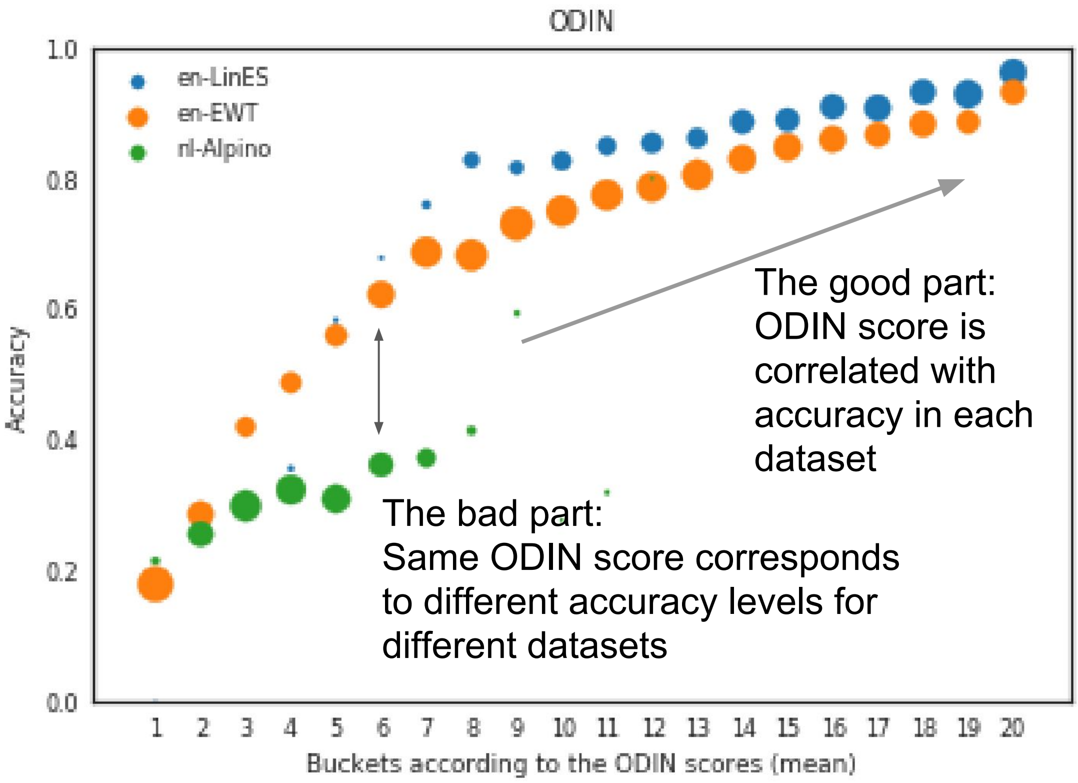


The good part:
ODIN score is correlated with accuracy in each dataset

The bad part:
Same ODIN score corresponds to different accuracy levels for different datasets

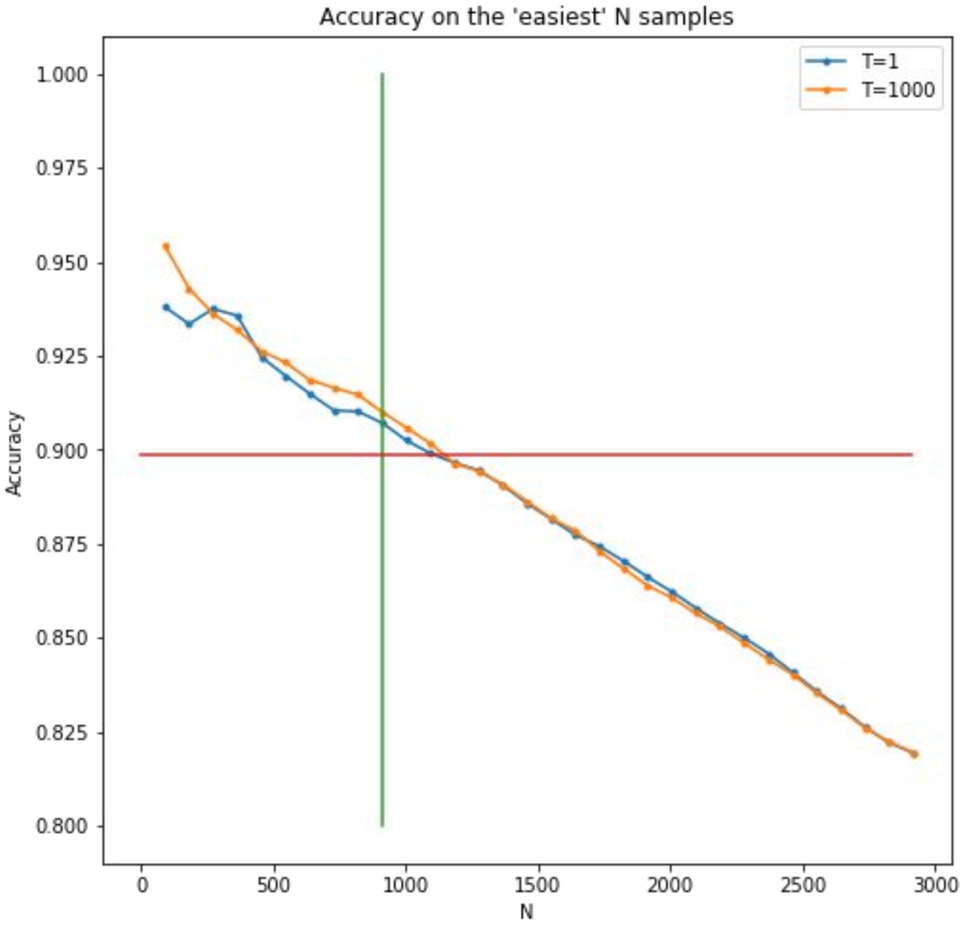
Thanks

https://yerevann.com

YN^2

Part-of-speech tagging

ODIN score can be used as a confidence measure on both datasets.


Accuracy on the 'easiest' N samples
T=1
T=1000
Accuracy
N