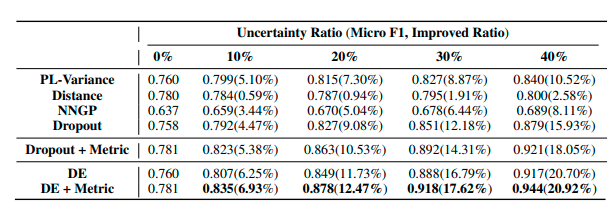
*Paper*: **Mitigating uncertainty in Document Classification**   
*Authors: Xuchao Zhang, Fanglan Chen, Chang-Tien Lu, Naren Ramakrishnan*  
*Published:* 2019 NAACL 2019  
*Label: Predictive Uncertainty* (WP3)

## **Theory** (type of innovation, improving X, task(s) description, uniqueness)

* Uncertainty estimation designed for text classification with focus on improving accuracy in HIL (human in the loop) budget learning.
* Metric learning, learning distance between feature representations.
* Dropout-entropy method (with denoising mask operations [rather unclear why/how this works]).

“our model improved the accuracy from 0.78 to 0.92 when 30% of the most uncertain predictions were handed over to human experts in “20NewsGroup” data” → uof 70% met 8%FP? 100 -22   
**2% FP difference with CNN MC dropout.**

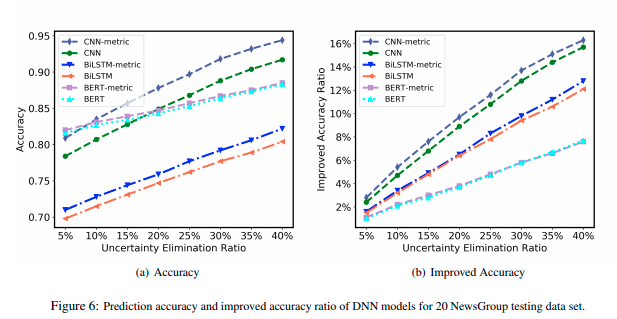


Instead of thresholding uncertainty/confidence, they select by X% most uncertainty (which you cannot know and do at inference time!).

## Methodology (support for claims, dataset, evaluation metrics):

20news dataset, IMDB binary movie reviews, Amazon reviews

Accuracy at %uncertainty reduction → no mention of support at reduced operating point.  
Report in terms of macro & micro F1, no calibration metrics.   
Compare with more exotic uncertainty estimation works.

Best comparison is on the usefulness of metric learning given different base architectures:

## **Open-source** material (code, dataset, tutorial, references):

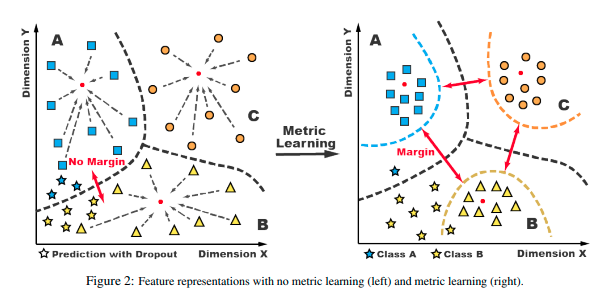
<https://github.com/xuczhang/UncertainDC><https://vimeo.com/347415373>

## Usefulness (task [classification, extraction, …], part-of-pipeline, extension / improvement on, domain/use-case):

**Document** classification

Metric learning is an interesting track to follow; inspired by Conformal Prediction.

Auxiliary loss function definition is very clear, albeit sloppily defined in arbitrary mathematical symbols.  
“Feature closeness” and complex classification boundaries are pervasive phenomena in text classification

****

## **Feasibility** (short-term/long-term | nice-to-have, complexity / far-from-practice)

Code is available, pytorch, easily readable.   
However, doing this in TF will be more complex as we need access to features while training, so requires custom training loop.

## Questions/Ideas

* Paper on automation formulas and operating points
* Why is it that BERT does not score better than Glove+CNN (rand) and metric learning?
  + It cannot benefit from the metric learning for which reason?

**BIBtex:**

```

@inproceedings{zhang-etal-2019-mitigating,

title = "Mitigating Uncertainty in Document Classification",

author = "Zhang, Xuchao and

Chen, Fanglan and

Lu, Chang-Tien and

Ramakrishnan, Naren",

booktitle = "Proceedings of the 2019 Conference of the North {A}merican Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)",

month = jun,

year = "2019",

address = "Minneapolis, Minnesota",

publisher = "Association for Computational Linguistics",

url = "https://www.aclweb.org/anthology/N19-1316",

doi = "10.18653/v1/N19-1316",

pages = "3126--3136",

abstract = "The uncertainty measurement of classifiers{'} predictions is especially important in applications such as medical diagnoses that need to ensure limited human resources can focus on the most uncertain predictions returned by machine learning models. However, few existing uncertainty models attempt to improve overall prediction accuracy where human resources are involved in the text classification task. In this paper, we propose a novel neural-network-based model that applies a new dropout-entropy method for uncertainty measurement. We also design a metric learning method on feature representations, which can boost the performance of dropout-based uncertainty methods with smaller prediction variance in accurate prediction trials. Extensive experiments on real-world data sets demonstrate that our method can achieve a considerable improvement in overall prediction accuracy compared to existing approaches. In particular, our model improved the accuracy from 0.78 to 0.92 when 30{\%} of the most uncertain predictions were handed over to human experts in {``}20NewsGroup{''} data.",

}

```