

Introducing gobbli

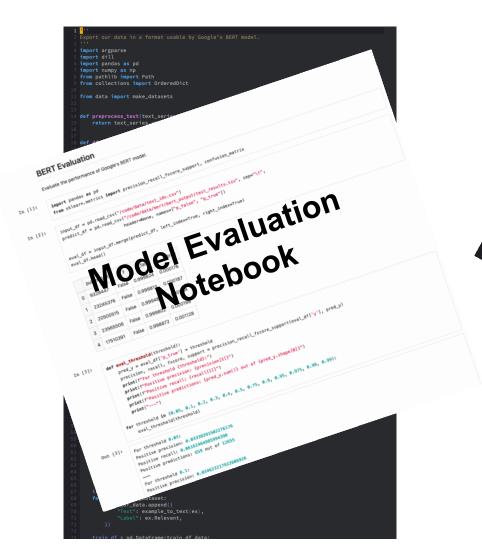
Deep learning with text doesn't have to be scary

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Using a State of the Art Model for Text Classification

Line Count: 0 101 108 142 167 187





Deep Learning: State of the Art

Best Scores on DBpedia Classification Benchmark*

- 2015: Char-level CNN (https://arxiv.org/abs/1509.01626v3)
- 2016: fastText (https://arxiv.org/abs/1602.02373v2)
 (https://arxiv.org/abs/1602.02373v2)
- 2017: DPCNN (https://www.aclweb.org/anthology/papers/P/P17/P17-1052/)
 1052/), M-ACNN (https://arxiv.org/abs/1709.08294v3)
- 2018: ULMFiT (https://arxiv.org/abs/1801.06146v5)
- 2019: BERT (https://arxiv.org/abs/1901.11504), MT-DNN (https://arxiv.org/abs/1901.11504), XLNet (https://arxiv.org/abs/1906.08237)

^{*} https://paperswithcode.com/sota/text-classification-on-dbpedia

The Problem: Hard-Coding for Benchmark Problems

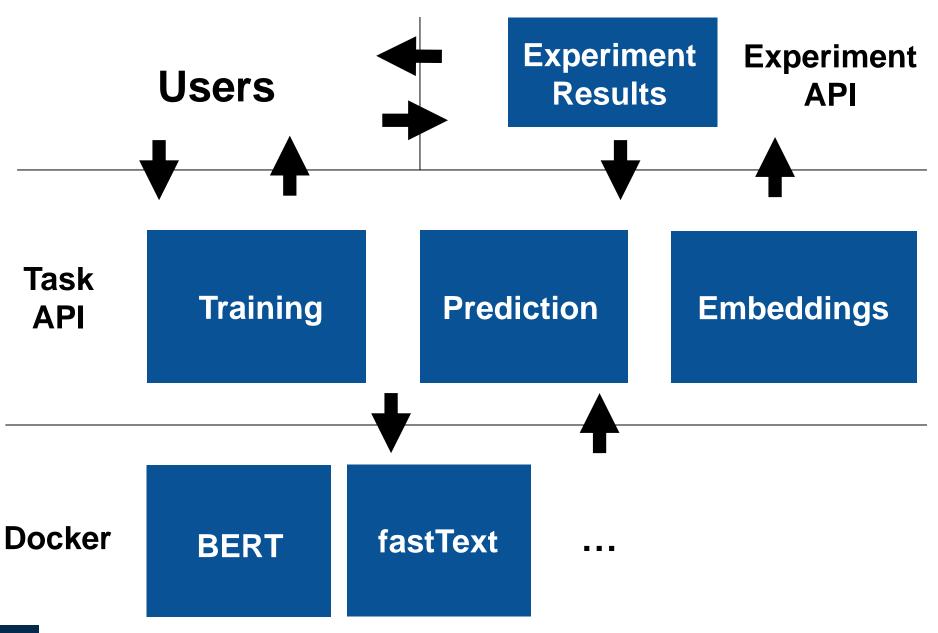
	Rank	c Name	Model	URL S	core (CoLA S	SST-2	MRPC	STS-B	QQP	MNLI-m MNLI-	mm	QNLI	RTE	WNL
	1	Microsoft D365 AI & UMD	Adv-RoBERTa (ensemble)		88.8	68.0	96.8	93.1/90.8	92.4/92.2	74.8/90.3	91.1	90.7	98.8	88.7	89.0
	2	Facebook Al	RoBERTa	Z	88.5	67.8	96.7	92.3/89.8	92.2/91.9	74.3/90.2	90.8	90.2	98.9	88.2	89.0
	3	XLNet Team	XLNet-Large (ensemble)	♂	88.4	67.8	96.8	93.0/90.7	91.6/91.1	74.2/90.3	90.2	89.8	98.6	86.3	90.4
+	4	Microsoft D365 AI & MSR A	I MT-DNN-ensemble	Z	87.6	68.4	96.5	92.7/90.3	91.1/90.7	73.7/89.9	87.9	87.4	96.0	86.3	89.0
	5	GLUE Human Baselines	GLUE Human Baselines		87.1	66.4	97.8	86.3/80.8	92.7/92.6	59.5/80.4	92.0	92.8	91.2	93.6	95.9
+	6	王玮	ALICE large ensemble (Alibaba DAMO NLF	P)[[]	87.0	69.2	95.2	92.6/90.2	91.1/90.6	74.4/90.7	88.2	87.9	95.7	83.5	87.0
	7	Stanford Hazy Research	Snorkel MeTaL	Z	83.2	63.8	96.2	91.5/88.5	90.1/89.7	73.1/89.9	87.6	87.2	93.9	80.9	65.
	8	XLM Systems	XLM (English only)	Z	83.1	62.9	95.6	90.7/87.1	88.8/88.2	73.2/89.8	89.1	88.5	94.0	76.0	71.9
	9	Zhuosheng Zhang	SemBERT		82.9	62.3	94.6	91.2/88.3	87.8/86.7	72.8/89.8	87.6	86.3	94.6	84.5	65.
	10	Danqi Chen	SpanBERT (single-task training)	♂	82.8	64.3	94.8	90.9/87.9	89.9/89.1	71.9/89.5	88.1	87.7	94.3	79.0	65.
	11	Kevin Clark	BERT + BAM	Z	82.3	61.5	95.2	91.3/88.3	88.6/87.9	72.5/89.7	86.6	85.8	93.1	80.4	65.
	12	Nitish Shirish Keskar	Span-Extractive BERT on STILTs		82.3	63.2	94.5	90.6/87.6	89.4/89.2	72.2/89.4	86.5	85.8	92.5	79.8	65.
	13	Jason Phang	BERT on STILTs		82.0	62.1	94.3	90.2/86.6	88.7/88.3	71.9/89.4	86.4	85.6	92.7	80.1	65.
	14	廖亿	RGLM-base (Huawei Noah's Ark Lab)		81.0	55.1	94.2	90.7/87.7	89.5/88.7	72.2/89.4	85.6	85.1	92.1	78.5	65.
+	15	Jacob Devlin	BERT: 24-layers, 16-heads, 1024-hidden		80.5	60.5	94.9	89.3/85.4	87.6/86.5	72.1/89.3	86.7	85.9	92.7	70.1	65.

https://gluebenchmark.com/leaderboard/

gobbli: A Uniform Interface for Text Deep Learning Models

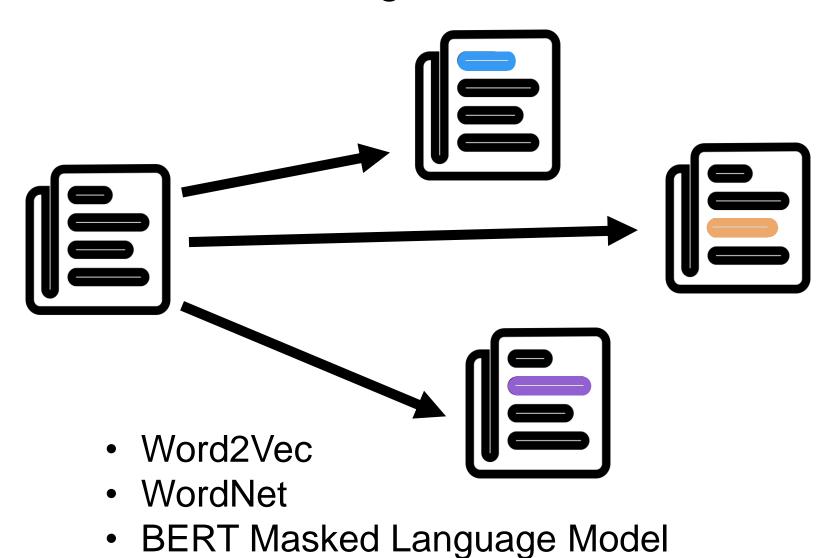


gobbli: Library Design



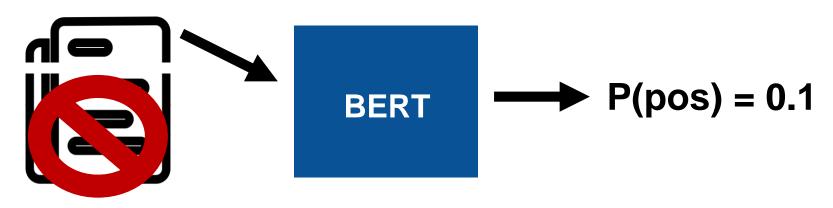
gobbli: Additional Features

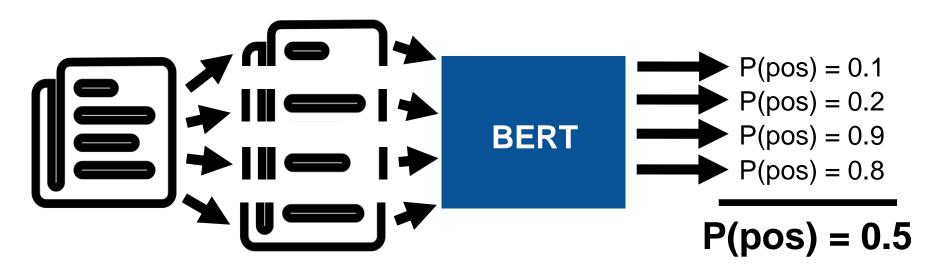
Data Augmentation



gobbli: Additional Features

Document Windowing





gobbli: Benefits and Drawbacks



- + Cross-platform
- + Abstracts dependency management
- Latency/overhead



- + Parallel/distributed training
- Experiment API only

Example Experiment Results

Example Experiment Results: Metrics

Metrics:

Weighted F1 Score: 0.8806791429898766

Weighted Precision Score: 0.8806909370983464

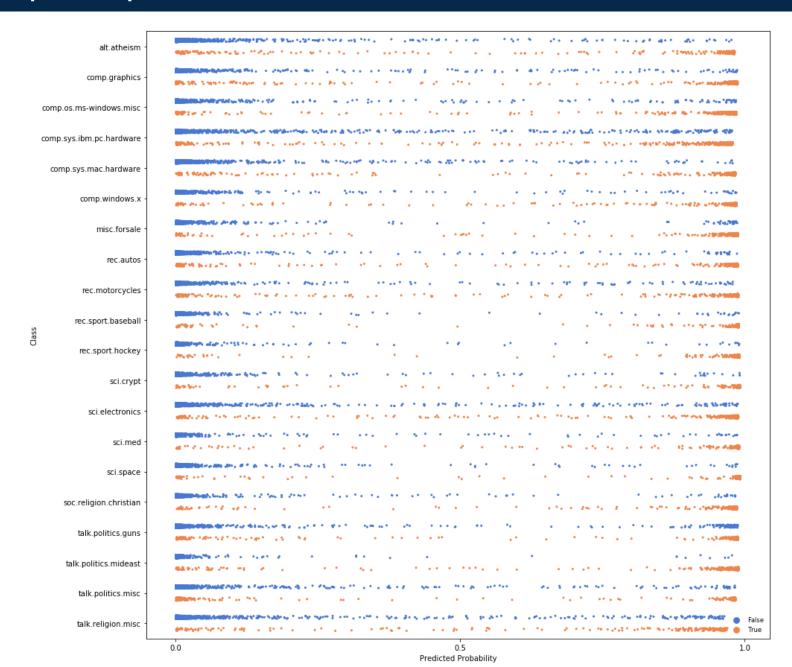
Weighted Recall Score: 0.88068

Accuracy: 0.88068

Classification Report:

	precision	recall	f1-score	support
neg pos	0.88	0.88 0.88	0.88 0.88	12500 12500
accuracy macro avg weighted avg	0.88 0.88	0.88 0.88	0.88 0.88 0.88	25000 25000 25000

Example Experiment Results: Plot



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Example Experiment Results: Errors Report

True Class: comp.os.ms-windows.misc

Predicted Class: sci.med (Probability: 0.97)

Text:

"My wife is a physiotherapist and she is looking for some cliparts of skeleton and male/female body. We're currently using Windows Draw which can import all kind of graphic formats. Therefore, anything will do. Please advise ..."

gobbli: Status and Next Steps

- Initial open source release on GitHub
 - <u>https://github.com/RTIInternational/gobbli/</u>
 - Models implemented: BERT, MT-DNN, USE, fastText, pytorch_transformers (XLNet, XLM, BERT, RoBERTa)
- Next steps:
 - Support multilabel classification
 - Helper module for downstream tasks using embeddings
 - Helper module for exploratory descriptives
 - Other bug fixes/enhancements requested by the community

Contact Information



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