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fastText

a library for efficient text classification and word representation

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Collaborators

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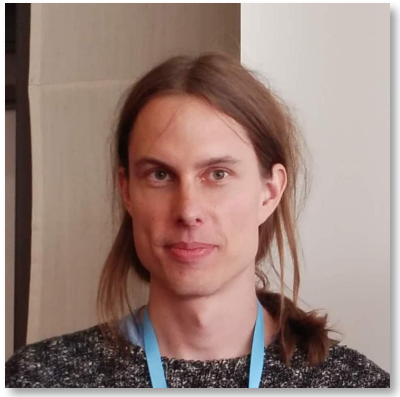
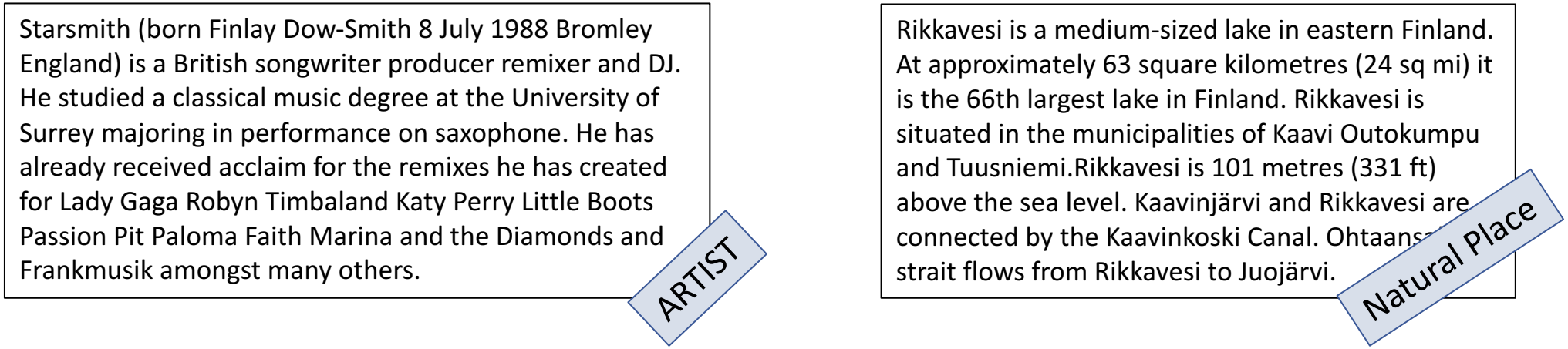


Tomáš Mikolov

Bag of Tricks for Efficient Text Classification

Fast text classification

- BoW model on text classification and tag prediction



- A very strong (and fast) baseline, often on-par with SOTA approaches
- Ease of use is at the core of the library

```
./fasttext supervised -input data/dbpedia.train -output data/dbpedia

./fasttext test data/dbpedia.bin data/dbpedia.test
```

Model

- Model probability of a label given a paragraph

feature for paragraph $\mathcal{P}$: $h_{\mathcal{P}}$
classifier for label l: v_l

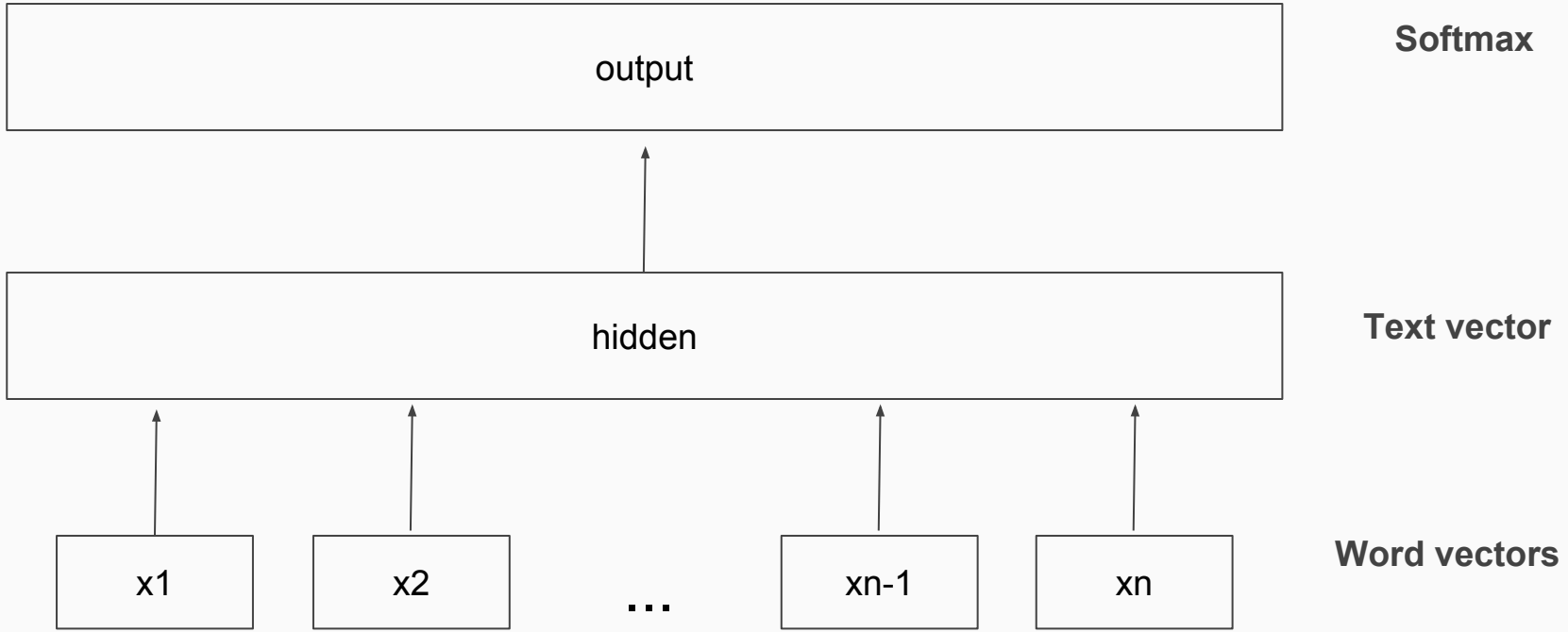
$$p(l|\mathcal{P}) = \frac{e^{h_{\mathcal{P}}^\top v_l}}{\sum_{k=1}^{K} e^{h_{\mathcal{P}}^\top v_k}}$$

- Paragraph feature

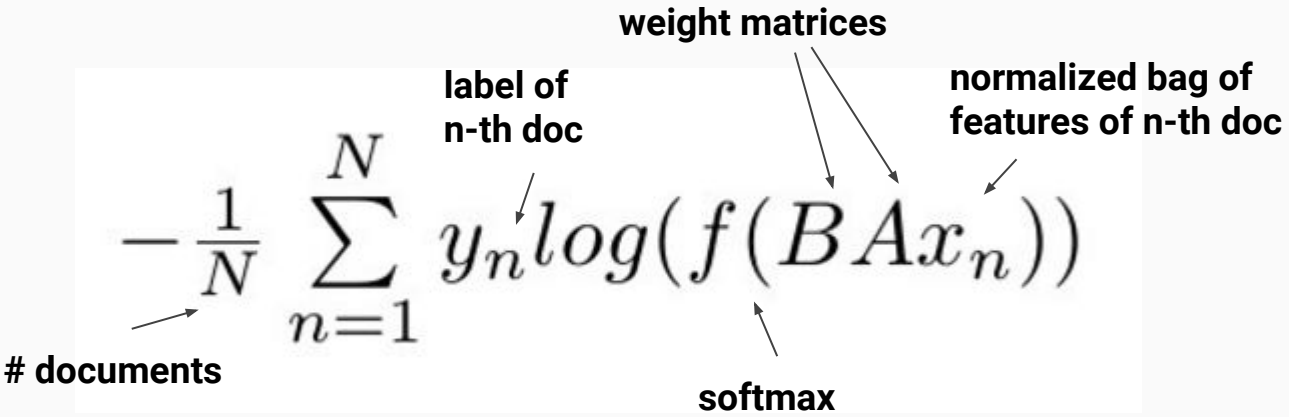
$$h_{\mathcal{P}} = \sum_{w \in \mathcal{P}} x_w$$

- Word vectors are latent and not useful *per se*
- If scarce supervised data, use pre-trained word vectors

Simple linear model



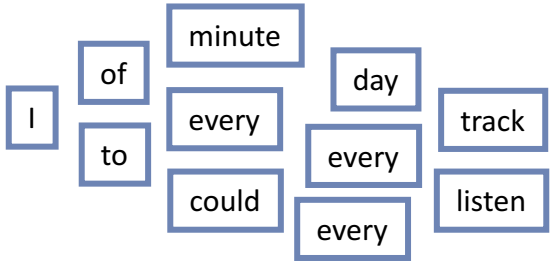
Learning

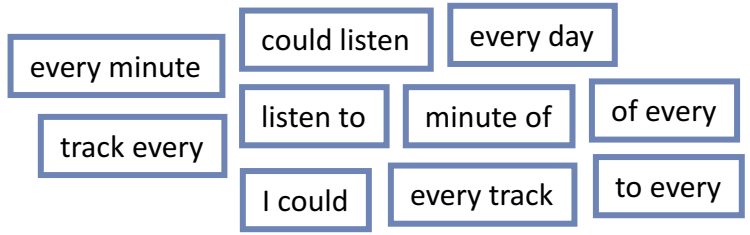

weight matrices
label of
n-th doc
normalized bag of
features of n-th doc
$-\frac{1}{N}\sum_{n=1}^{N} y_n log(f(BAx_n))$
documents
softmax

n-grams

- Possible to add higher-order features

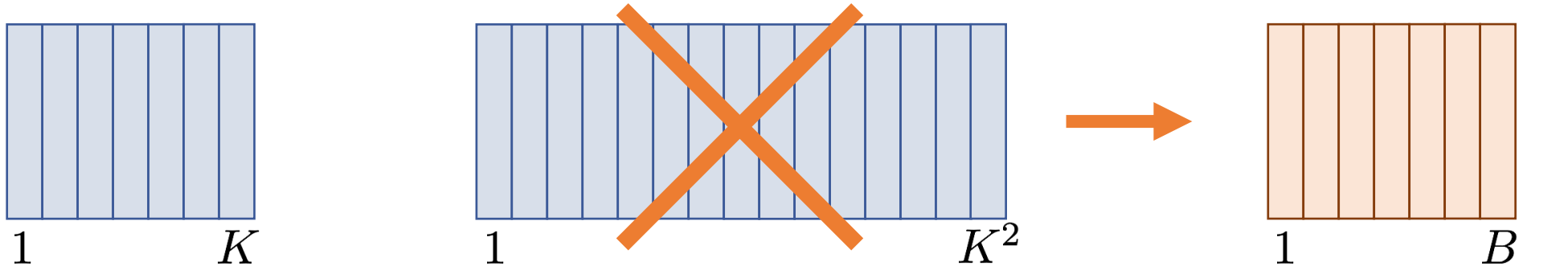
I could listen to every track every minute of every day.





- Avoid building n-gram dictionary

Use a hashed dictionary!



Sentiment analysis - performance

Model	AG	Sogou	DBP	Yelp P.	Yelp F.	Yah. A.	Amz. F.	Amz. P.
BoW (Zhang et al., 2015)	88.8	92.9	96.6	92.2	58.0	68.9	54.6	90.4
ngrams (Zhang et al., 2015)	92.0	97.1	98.6	95.6	56.3	68.5	54.3	92.0
ngrams TFIDF (Zhang et al., 2015)	92.4	97.2	98.7	95.4	54.8	68.5	52.4	91.5
char-CNN (Zhang and LeCun, 2015)	87.2	95.1	98.3	94.7	62.0	71.2	59.5	94.5
char-CRNN (Xiao and Cho, 2016)	91.4	95.2	98.6	94.5	61.8	71.7	59.2	94.1
VDCNN (Conneau et al., 2016)	91.3	96.8	98.7	95.7	64.7	73.4	63.0	95.7
`fastText`, h = 10	91.5	93.9	98.1	93.8	60.4	72.0	55.8	91.2
`fastText`, h = 10, bigram	92.5	96.8	98.6	95.7	63.9	72.3	60.2	94.6

Table 1: Test accuracy [%] on sentiment datasets. `FastText` has been run with the same parameters for all the datasets. It has 10 hidden units and we evaluate it with and without bigrams. For char-CNN, we show the best reported numbers without data augmentation.

Sentiment analysis - runtime

	Zhang and LeCun (2015)		Conneau et al. (2016)			`fastText`
	small char-CNN	big char-CNN	depth=9	depth=17	depth=29	h = 10, bigram
AG	1h	3h	24m	37m	51m	1s
Sogou	-	-	25m	41m	56m	7s
DBpedia	2h	5h	27m	44m	1h	2s
Yelp P.	-	-	28m	43m	1h09	3s
Yelp F.	-	-	29m	45m	1h12	4s
Yah. A.	8h	1d	1h	1h33	2h	5s
Amz. F.	2d	5d	2h45	4h20	7h	9s
Amz. P.	2d	5d	2h45	4h25	7h	10s

Table 2: Training time for a single epoch on sentiment analysis datasets compared to char-CNN and VDCNN.

Tag prediction

- Using Flickr Data
- Given an image caption
- Predict the most likely tag
- Sample outputs:

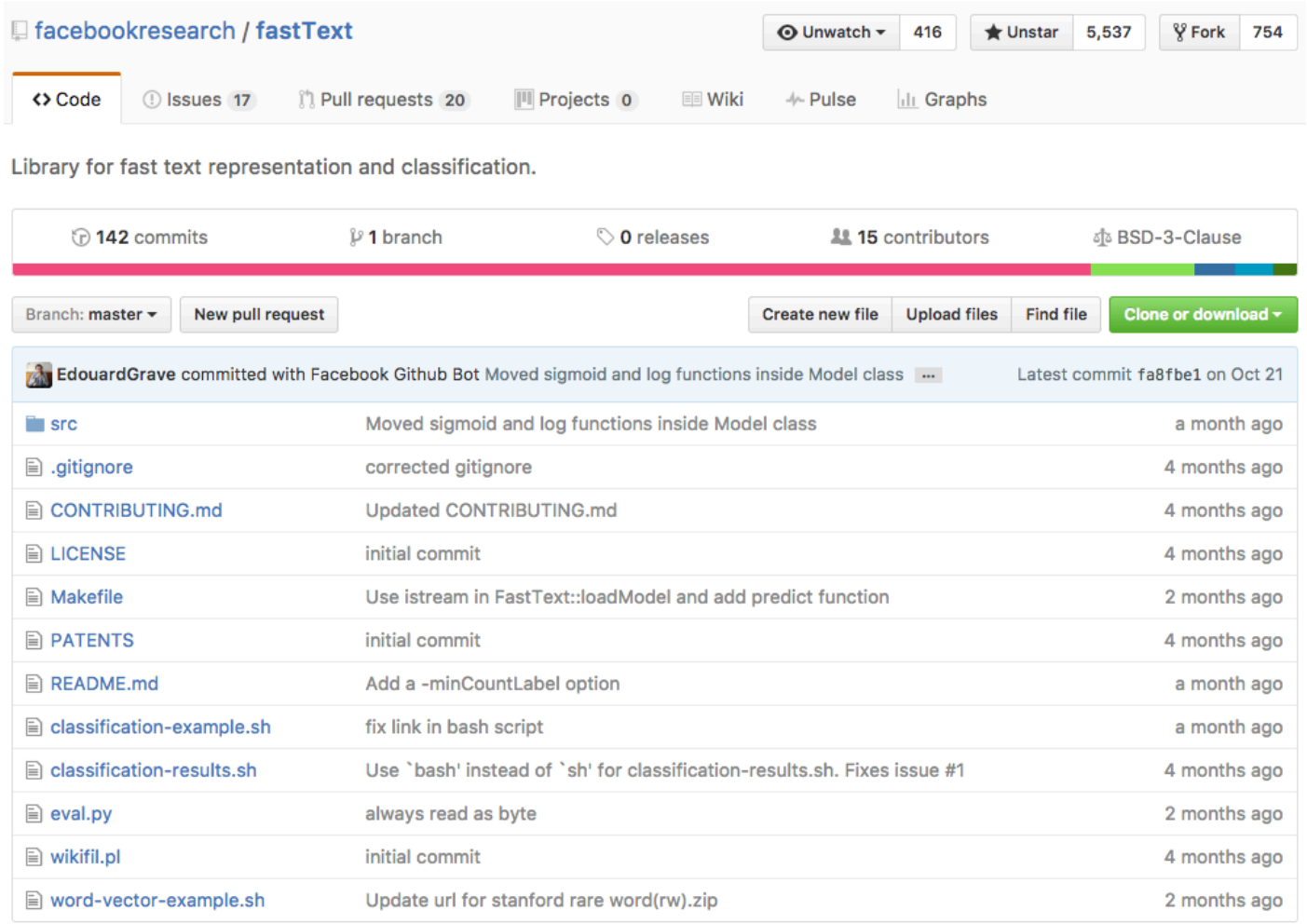
Input	Prediction
taiyoucon 2011 digitals: individuals digital photos from the anime convention taiyoucon 2011 in mesa, arizona. if you know the model and/or the character, please comment.	#cosplay
2012 twin cities pride 2012 twin cities pride parade	#minneapolis
beagle enjoys the snowfall	#snow

Model	prec@1	Running time	
		Train	Test
Freq. baseline	2.2	-	-
Tagspace, h = 50	30.1	3h8	6h
Tagspace, h = 200	35.6	5h32	15h
`fastText`, h = 50	31.2	6m40	48s
`fastText`, h = 50, bigram	36.7	7m47	50s
`fastText`, h = 200	41.1	10m34	1m29
`fastText`, h = 200, bigram	46.1	13m38	1m37

Table 5: Prec@1 on the test set for tag prediction on YFCC100M. We also report the training time and test time. Test time is reported for a single thread, while training uses 20 threads for both models.

fasttext is open source

- Available on Github
  - After 6 months:
    - > 6700 stars!
    - 1.6k members FB group
- Featured in “popular” press
- C++ code
- Bash scripts as examples
- Very simple usage
- Several OS projects
  - Python wrapper
  - Docker files

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