

SECTOR: A Neural Model for Coherent Topic Segmentation and Classification

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Transactions of the Association for
Computational Linguistics (TACL) Vol.7

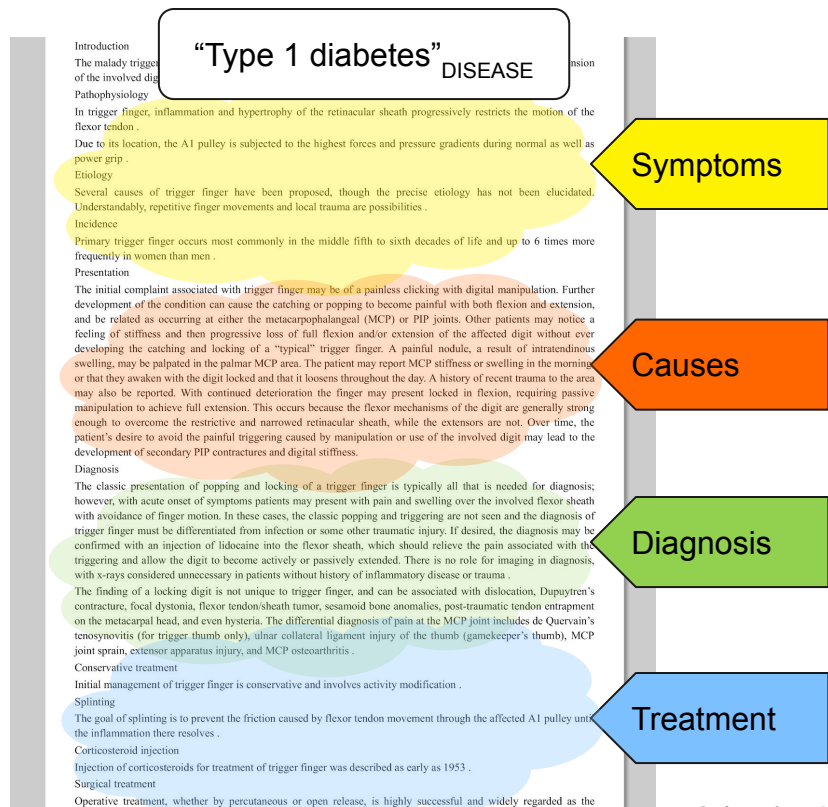
ACL 2019, Florence, Italy

29.07.2019

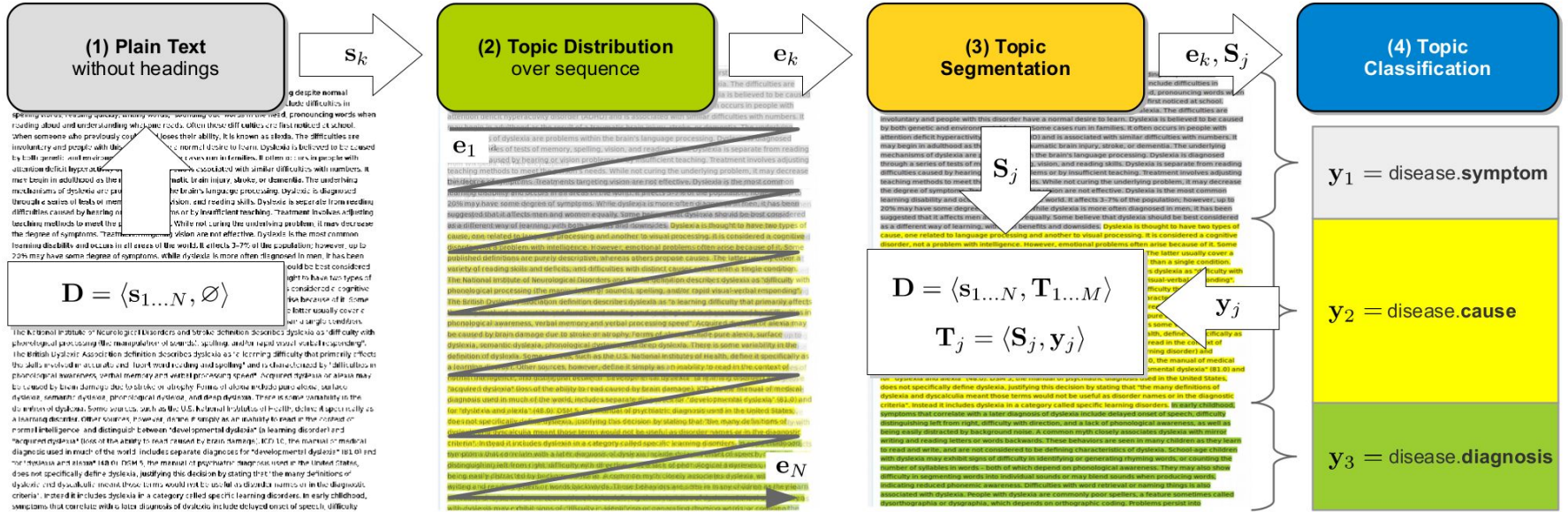
Challenge: understand the topics and structure of a document

How can we represent a document with respect to the author's emphasis?

- topical information [Ma18] (e.g. semantic class labels)
- structural information [Ag09, Gla16] (e.g. coherent passages)
- in latent vector space [Le14, Bha16] (i.e. distributional embedding)
- required for TDT, QA & IR downstream tasks [All02, Di07, Coh18]



Task: split a document into coherent sections with topic labels

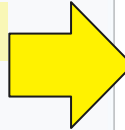


We aim to detect topics in a document that are expressed by the author as a coherent sequence of sentences (e.g., a passage or book chapter).

WikiSection: Wiki authors provide topics as section headings

Contents [hide]

- 1 Signs and symptoms
 - 1.1 Diabetic emergencies
 - 1.2 Complications
- 2 Causes
 - 2.1 Type 1
 - 2.2 Type 2
 - 2.3 Gestational diabetes
 - 2.4 Maturity onset diabetes of the young
 - 2.5 Other types
- 3 Pathophysiology
- 4 Diagnosis
- 5 Prevention
- 6 Management
 - 6.1 Lifestyle
 - 6.2 Medications
 - 6.3 Surgery
 - 6.4 Support
- 7 Epidemiology
- 8 History
 - 8.1 Etymology
- 9 Society and culture
 - 9.1 Naming
- 10 Other animals
- 11 Research
- 12 References
- 13 Further reading
- 14 External links



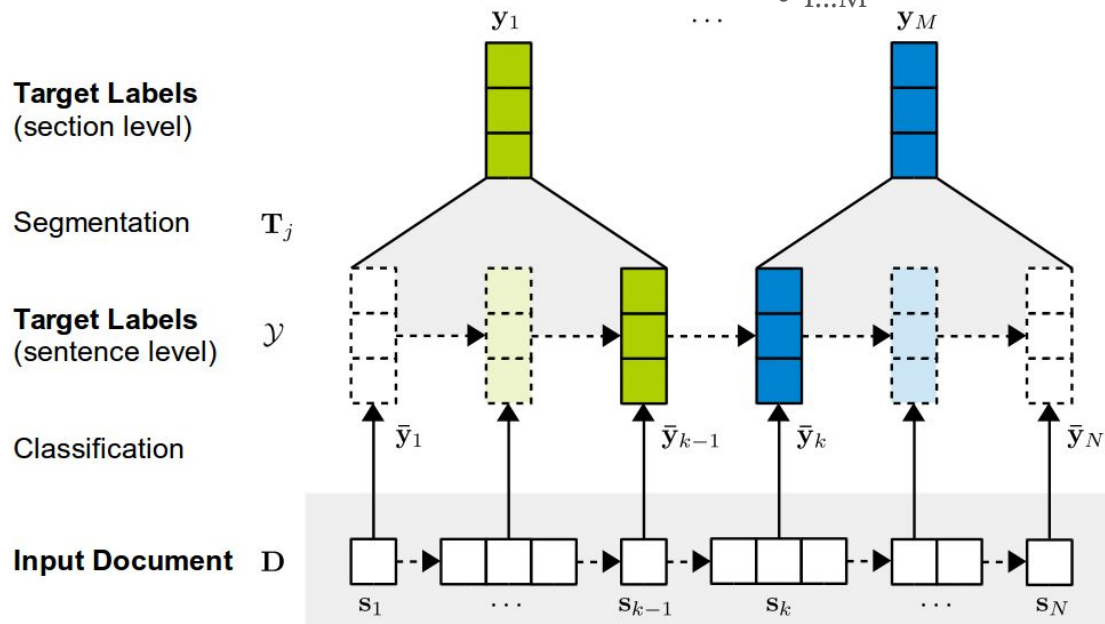
en_disease (27)	de_disease (25)
treatment	therapie
symptom	diagnose
diagnosis	symptom
cause	ursache
classification	kategorisierung
epidemiology	verlauf
history	epidemiologie
prognosis	geschichte
management	prognose
pathophysiology	praevalenz
mechanism	vorbeugung
prevention	fauna
research	terminologie
genetics	pathologie
tomography	definition
culture	klinik
etymology	komplikation
infection	genetik
fauna	infektion
risk	risiko
pathology	forschung
surgery	geographie
screening	mensch
medication	organe
geography	sonstiges
complication	
other	

en_disease	de_disease	en_city	de_city
3.6k English articles	2.3k German articles	19.5k English articles	12.5k German articles
8.5k headings	6.1k headings	23.0k headings	12.2k headings
27 topics (94.6%)	25 topics (89.5%)	30 topics (96.6%)	27 topics (96.1%)

<https://github.com/sebastianarnold/WikiSection>

SECTOR sequential prediction approach

- Transform a document of N sentences $\mathbf{s}_{1..N}$ into N topic distributions $\bar{\mathbf{y}}_{1..N}$
- Predict M sections $\mathbf{T}_{1..M}$ based on coherence of the network's weights
- Assign section-level topic labels $\mathbf{y}_{1..M}$



Number and length of sections is unknown!

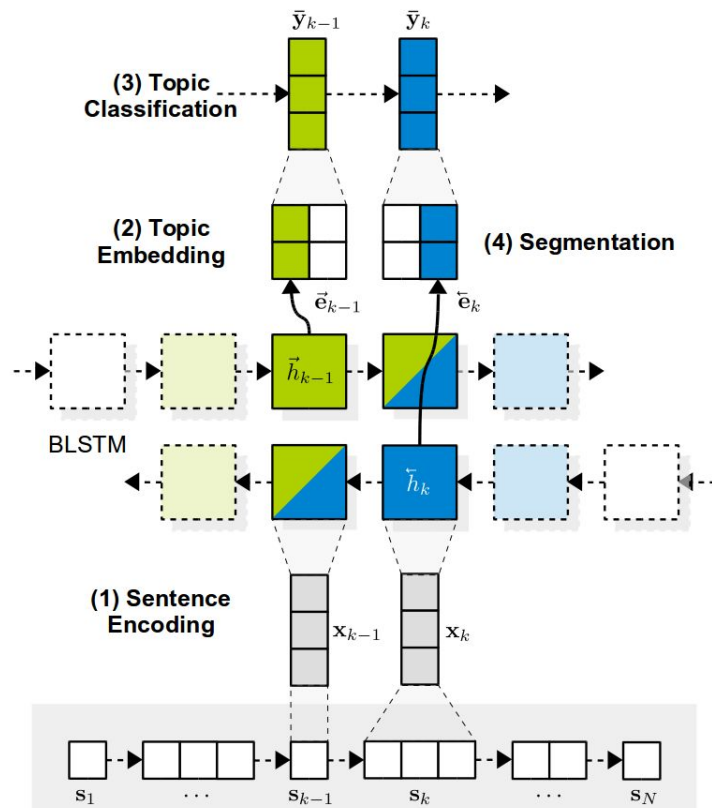
$$p(\bar{\mathbf{y}}_1, \dots, \bar{\mathbf{y}}_N \mid \mathbf{D}) = \prod_{k=1}^N p(\bar{\mathbf{y}}_k \mid \mathbf{s}_1, \dots, \mathbf{s}_N)$$

Network architecture (0/4) – Overview

Objective: maximize the log likelihood of model parameters Θ per document on sentence-level

$$\bar{\mathcal{L}}(\Theta) = \sum_{k=1}^N \log p(\bar{\mathbf{y}}_k \mid \mathbf{s}_1, \dots, \mathbf{s}_N; \Theta)$$

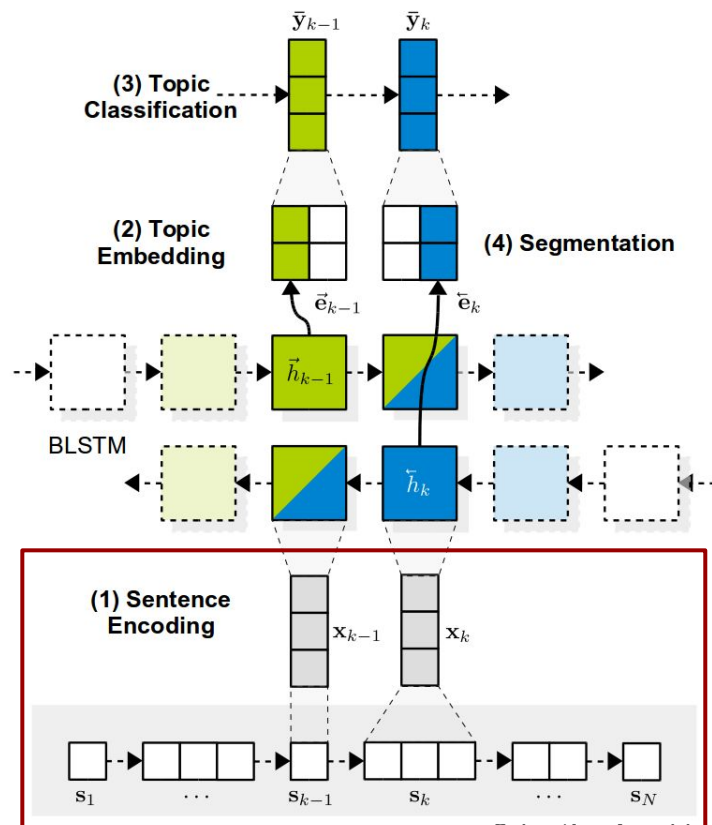
- Requires the entire document as input
- Long range dependencies
- Focus on sharp distinction at topic shifts



Network architecture (1/4) – Sentence encoding

Input: Vector representation of a full document

- Split text into sequence of sentences $s_{1\dots N}$
- Encode sentence vectors $\mathbf{x}_{1\dots N}$ using
 - Bag-of-words (~56k english words)
 - Bloom filter (4096 bits) [Se17] or
 - Pre-trained sentence embeddings [Mik13, Aro17] (128 dim)
- Use sentences as time-steps



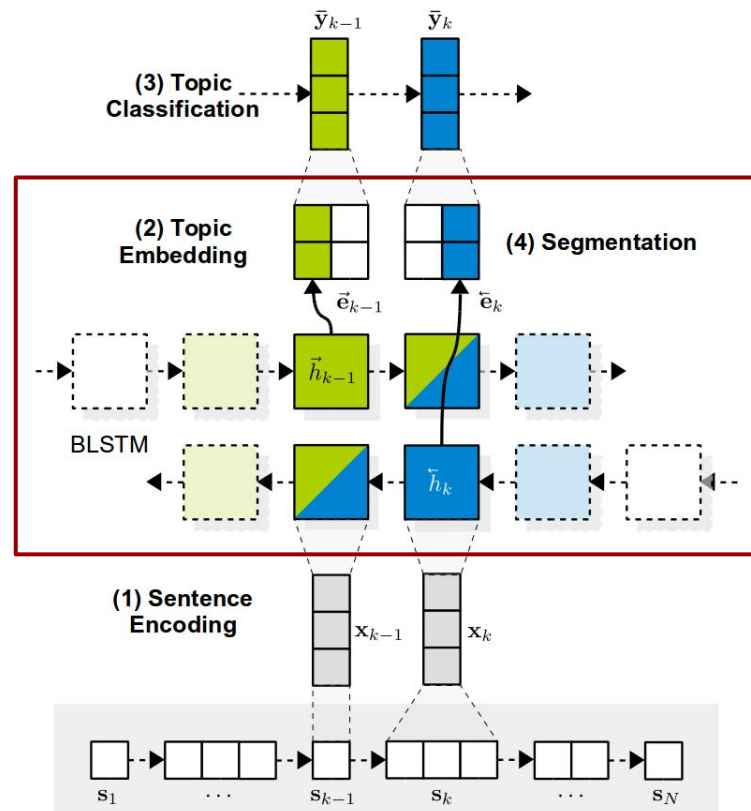
Network architecture (2/4) – Topic embedding

Encoder: Bidirectional Long Short-Term Memory (BLSTM) [Ho97, Ge00, Gra12] + dense embedding layer

- independent *fw* and *bw* parameters $\vec{\Theta}, \vec{\Theta}'$ helps to sharpen left/right context
- embedding layer captures latent topics

$$\mathcal{L}(\Theta) = \sum_{k=1}^N \left(\log p(\bar{y}_k \mid \mathbf{x}_{1\dots k-1}; \vec{\Theta}, \Theta') \right. \\ \left. + \log p(\bar{y}_k \mid \mathbf{x}_{k+1\dots N}; \vec{\Theta}, \Theta') \right)$$

- 2x256 LSTM cells, 128 dim embedding layer, 16 docs per batch, 0.5 dropout, ADAM opt.



Network architecture (3/4) – Topic classification

Output layer: Classification

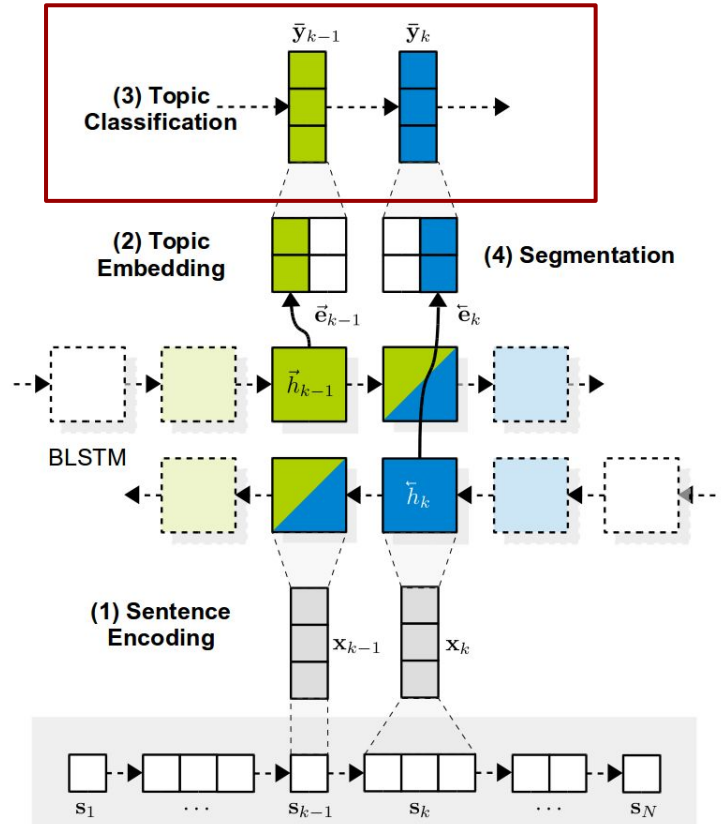
- Decodes target probabilities
- Human-readable topic labels for 2 Tasks:

- **topic classes** $\bar{y}_{1..N}$ (25–30 topics)
disease.symptom

$$\hat{\bar{y}}_k = \text{softmax}(W_{ye} \vec{e}_k + W_{ye} \vec{e}_k + b_y)$$

- **headline words** $\bar{z}_{1..N}$ (1.5–2.8k words)
[signs, symptoms]

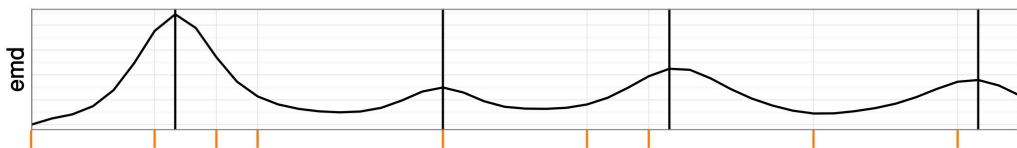
$$\hat{\bar{z}}_k = \text{sigmoid}(W_{ze} \vec{e}_k + W_{ze} \vec{e}_k + b_z)$$



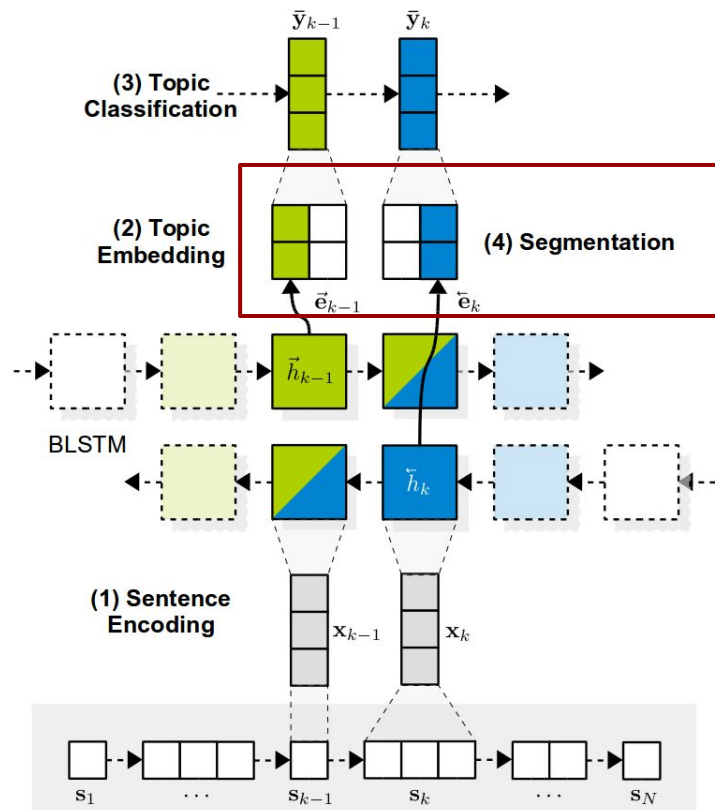
Network architecture (4/4) – Segmentation

Segmentation: based on topic coherence

- deviation d'_k : stepwise “movement” of the embedding between two sentences

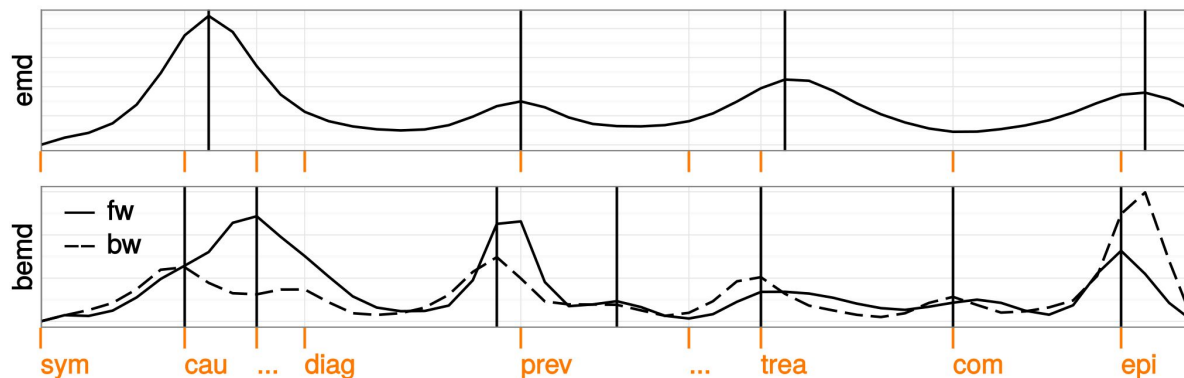


$$d'_k = \sqrt{\cos(\vec{e}'_{k-1}, \vec{e}'_k) \cdot \cos(\vec{e}'_k, \vec{e}'_{k+1})}$$



Coherent segmentation using edge detection

We use the topic embedding deviation (emd) d_k to start new segments on peaks.



- Idea adapted from image processing: we apply *Laplacian-of-Gaussian edge detection* [zi:98] to find local maxima on the emd curve
- Steps: dimensionality reduction (PCA), Gaussian smoothing, local maxima
- Bidirectional deviation (bemd) on *fw* and *bw* layers allows for sharper separation

Experiments with 20 different models on 8 datasets

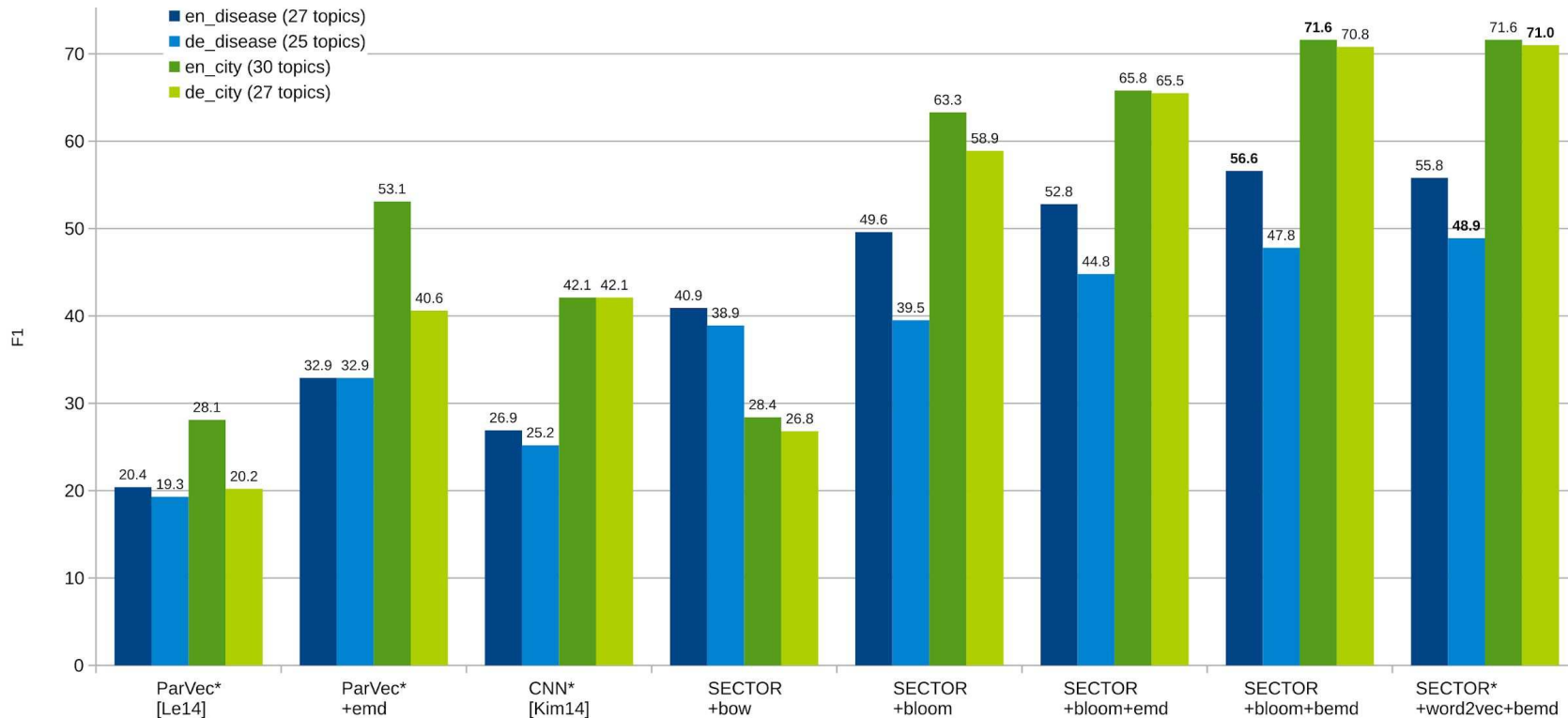
dataset	articles	article type	headings	topics	segments
WikiSection	38k train/test	German/English diseases and cities	X	X	X
Wiki-50 [Kosh18]	50 test	English generic	X		X
Cities/Elements [Chen09]	130 test	English cities and chemicals (lowercase)			X
Clinical Textbook [Eis08]	227 test	English clinical	X		X

Sentence Classification Baselines: ParVec [\[Le14\]](#), CNN [\[Kim14\]](#)

Segmentation Models: C99 [\[Choi00\]](#), TopicTiling [\[Rie12\]](#), BayesSeg [\[Eis08\]](#), TextSeg [\[Kosh18\]](#)

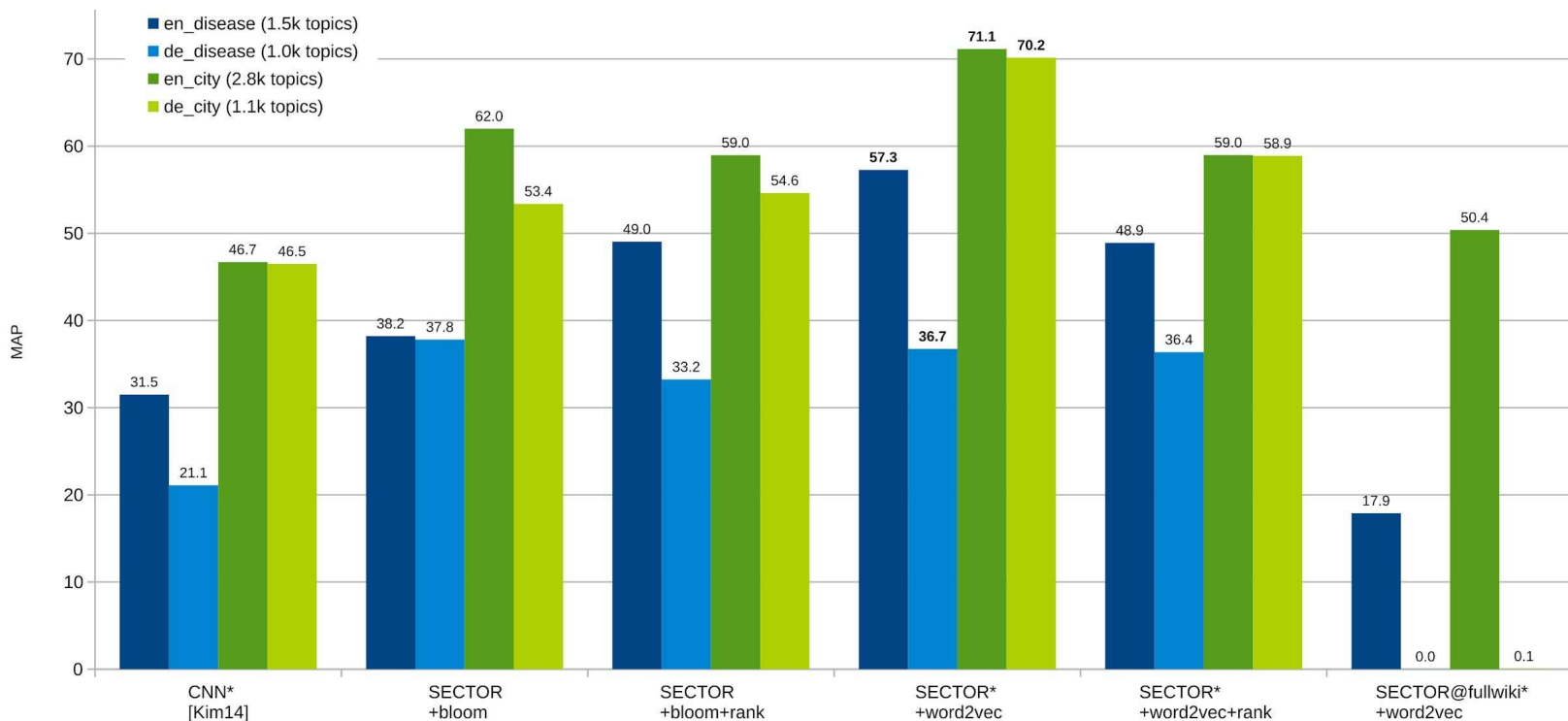
Experiment 1: segmentation and single-label classification

Segment on sentence-level and assign one of 25–30 supervised topic labels (F1)

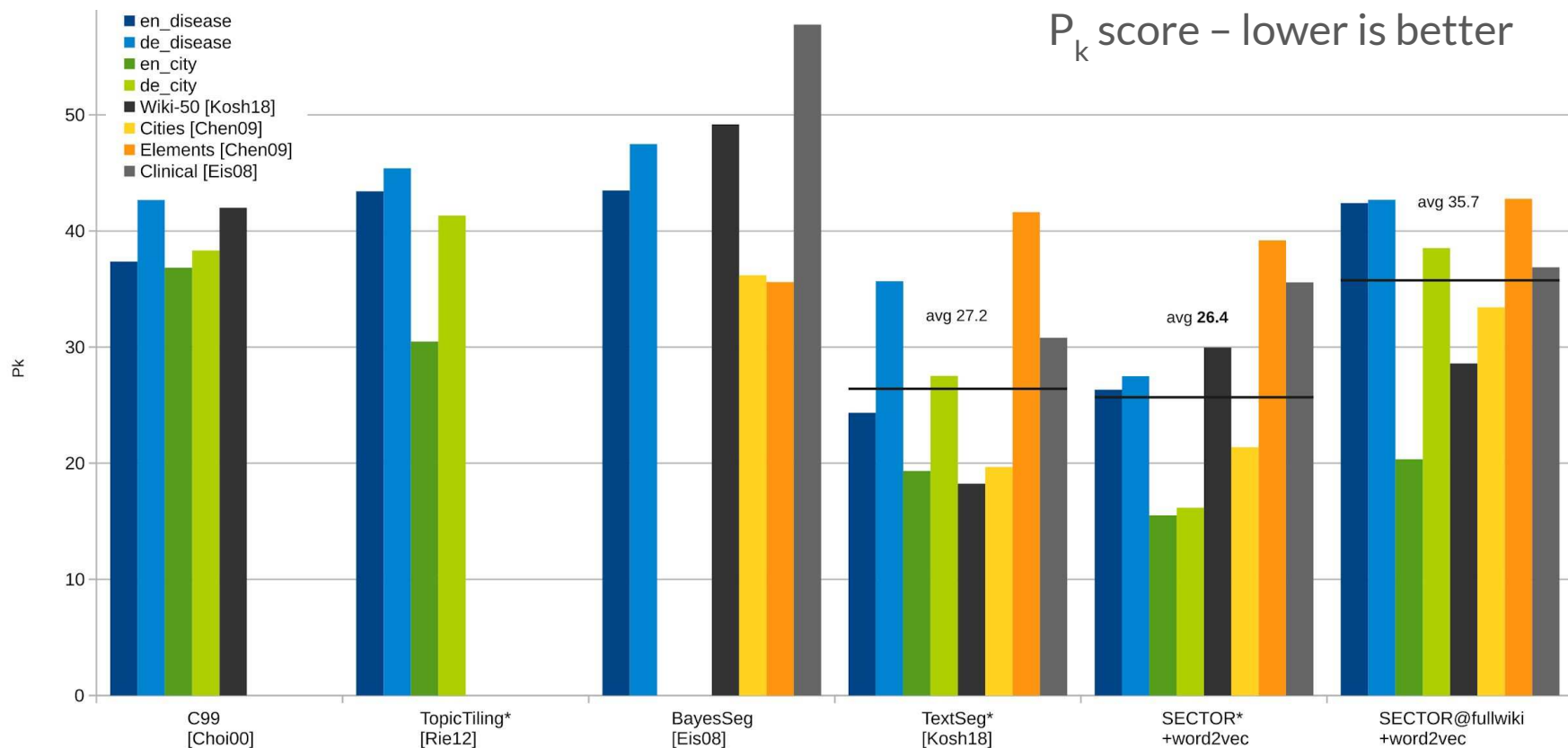


Experiment 2: segmentation and multi-label classification

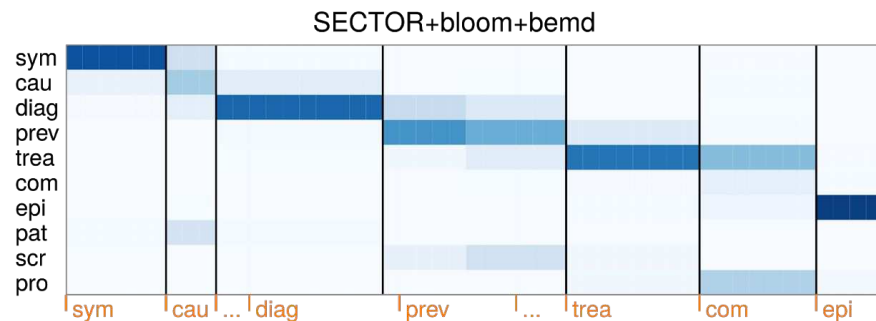
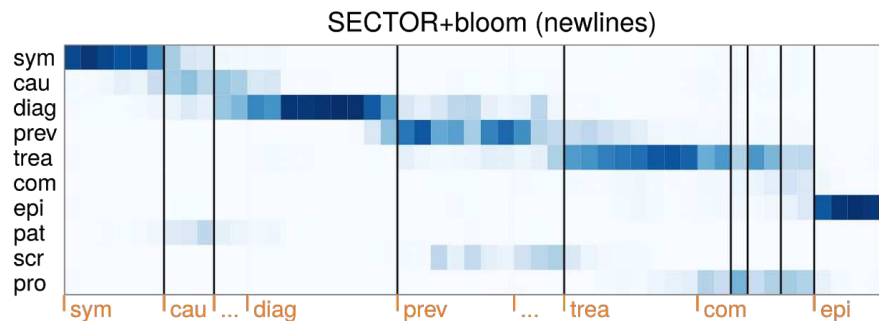
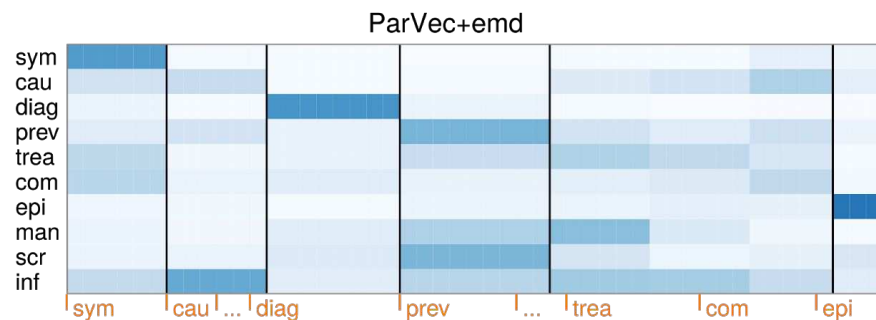
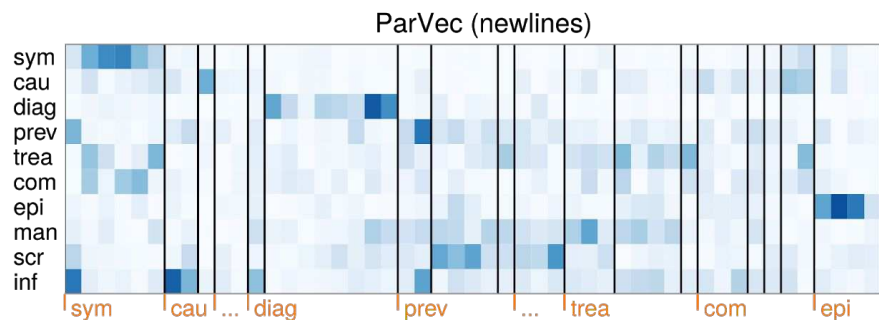
Segment on sentence-level and rank 1.0k–2.8k ‘noisy’ topic words per section (MAP)



Experiment 3: segmentation without topic prediction (cross-dataset)

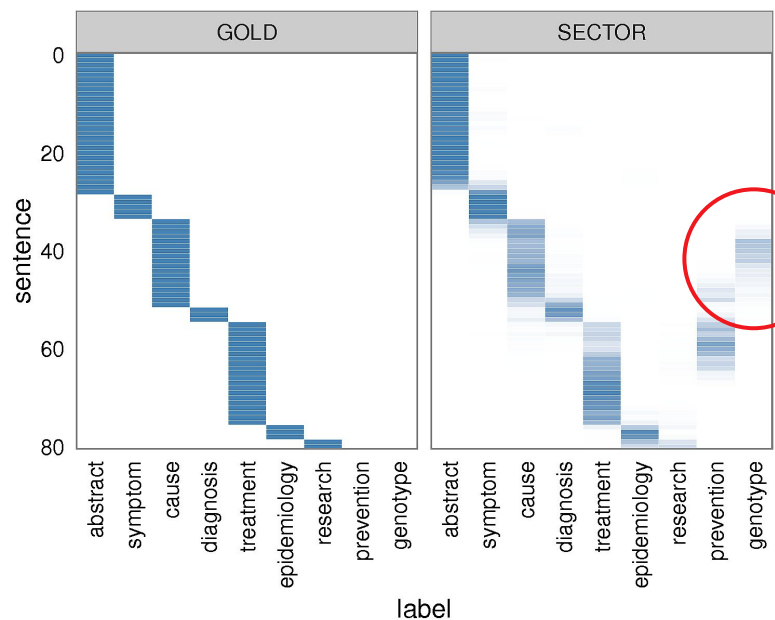


Insights: SECTOR captures topic distributions coherently



Topic predictions on sentence level – top: ParVec [Le14] – bottom: SECTOR Segmentation – left: newlines in text (\n) – right: embedding deviation (emd)

SECTOR prediction on par with Wiki authors for “dermatitis”



Browse history

Revision as of 02:24, 31 March 2017 (edit)
liibalesiii (talk | contribs)
(→Cause)
← Previous edit

Revision as of 02:27, 31 March 2017 (edit) (undo)
liibalesiii (talk | contribs)
(Causes was reorganized w/ better flow.)
(Tag: Visual edit)
Next edit →

Line 35:

== Causes ==

Many people with AD have a family history of [[atopy]]. Atopy is an immediate-onset allergic reaction (type 1 hypersensitivity reaction) as asthma, food allergies, AD or hay fever.<ref name = AFP/><ref name = MSR/> In 2006 it was discovered that [[mutation]]s in the gene for the production of [[filaggrin]] strongly increased the risk for developing atopic dermatitis. Most importantly two mutations were found that affect approximately 5% of people in Western Europe that may disrupt the production of filaggrin. Filaggrin is a protein that plays an important role in the retention of water in the [[stratum corneum]]. People who have these mutations often have [[xeroderma|dry

== Genetic ==

Source: https://en.wikipedia.org/w/index.php?title=Atopic_dermatitis&diff=786969806&oldid=772576326

Conclusion and future work

SECTOR is designed as a building block for document-level knowledge representation

- Reading sentences in document context is an important step to capture both **topical and structural information**
- Training the topic embedding with distant-supervised **complementary labels** improves performance over self-supervised word embeddings
- **In future work**, we aim to apply the topic embedding for unsupervised passage retrieval and QA tasks

The finding of a locking digit is not unique to trigger finger, and can be associated with dislocation, Dupuytren's contracture, focal dystonia, flexor tendon/sheath tumor, sesamoid bone anomalies, post-traumatic tendon entrapment on the metacarpal head, and even hysteria. The differential diagnosis of pain at the MCP joint includes de Quervain's tenosynovitis (for trigger thumb only), ulnar collateral ligament injury of the thumb (gamekeeper's thumb), MCP joint sprain, extensor apparatus injury, and MCP osteoarthritis .

Conservative treatment

Initial management of trigger finger is conservative and involves activity modification .

Splinting

The goal of splinting is to prevent the friction caused by flexor tendon movement through the area where the inflammation there resolves .

Corticosteroid injection

Injection of corticosteroids for treatment of trigger finger was described as early as 1953 .

Surgical treatment

Operative treatment, whether by percutaneous or open release, is highly successful and widely regarded as the ultimate treatment for trigger finger. Indication for surgical treatment is generally failure of conservative treatment to resolve pain and symptoms. The timing of surgery is somewhat controversial with data suggesting surgical consideration after failure of both a single as well as multiple corticosteroid injections .

The percutaneous trigger finger release has been described and was first introduced by Lorthioir in 1958 .

Open release of trigger finger has been used as treatment for over a century .

Conclusion

Trigger finger is a long recognized condition characterized by a sometimes painful locking of the digit on flexion and extension. It is caused by the inflammation and subsequent narrowing of the A1 pulley through which the flexor

q = "therapy"

Thanks & Questions

SECTOR: A Neural Model for Coherent Topic Segmentation and Classification

Code and dataset available on GitHub:

<https://github.com/sebastianarnold/SECTOR>

<https://github.com/sebastianarnold/WikiSection>

Our work is funded by the German Federal Ministry of Economic Affairs and Energy (BMWi) under grant agreement 01MD16011E (Medical Allround-Care Service Solutions) and H2020 ICT-2016-1 grant agreement 732328 (FashionBrain).

Gefördert durch:



aufgrund eines Beschlusses
des Deutschen Bundestages

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