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Sentence Centrality Revisited for Unsupervised Summarization

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論文URL:https://www.aclweb.org/anthology/P19-1628/ 提案手法ソースコード:https://github.com/mswellhao/PacSum

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概要

- やりたいこと:教師なし文書要約
- 提案手法:PAcSUM

(Position-Augmented Centrality based Summarization)

Centrality-based Summarization

- 文書を文をノードとする重み付きグラフで表現
 - 重み: 文間類似度
- グラフ上で重要な文を要約文として抽出
 - 重要度:次数中心性, PageRank, など
- ▶ 文間類似度
 - 文表現にBERT
 - 類似度に文表現の内積(cosine 類似度ではない)
- ▶ 有向グラフ
 - 文の(相対的な)出現位置を考慮:前に出てくる文ほど重要

教師あり	教師なし				
 性能・高 	 性能・低 				
 教師データが必要 	 教師データが不要 				

- ・近年の状況
 - 教師ありデータセット数が増加傾向
 - 言語や分野に網羅的なデータセットは望めない
- •教師なし文書要約は未だ重要
 - ・ 性能向上が必須

教師なし文書要約:グラフアプローチ

・代表的な手法:TextRank [Mihalcea+, 2004]



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Abstract

Single document summarization has enjoye enewed interest in recent years thanks to th sopularity of neural network models and th svaliability of large-scale datasets. In this pare we develop an unsupervised approach ar-guing that it is unrealistic to expect large-scale and high-quality training data to be available or created for different types of summaries, domains, or languages. We revisit a popu-lar graph-based ranking algorithm and mod-fiyhow node (also sentence) centrality is com-pated in two ways: (a) we employ DEET, a state-of the-art neural representation learning ailability of large-scale datasets. In this p sture sentential meaning and b) we build graphs with directed edges argu-ig that the contribution of any two nodes to ir respective centrality is influenced by their eir respective centrality is influenced by their lative position in a document. Experimental sults on three news summarization datasets presentative of different languages and writ-g styles show that our approach outperforms rong baselines by a wide margin.¹ 1 Introduction

Our code is available at https://github.com/

2004: Erkan and Radey 2004: Wan 2008: Wan and Yang, 2008; Hirao et al., 2013; Parveen et al., 2015: Yin and Pei 2015: Li et al. 2017). A sen 2015; Yin and Pei, 2015; Li et al., 2017). A very popular algorithm for extractive single-document summarization is TextRank (Mihaleea and Tarau, 2004); it represents document sentences as nodes in a graph with *undirected* edges whose weights are computed based on sentence similarity. In order to decide which sentence to include in the sum der to decide which sentence to include in the sum-mary, a node's *centrality* is often measured using graph-based ranking algorithms such as PageRank (Brin and Page, 1998). In this paper, we argue that the centrality measure can be improved in two important respects Firstly, to better capture sentential meaning and 1 Introduction Single-document summirization in the task of Single-document summirization in the task of generating a shorter version of a document while relating in sum output context (New Single-document sums). Second, Single-document sums, Single-document su spective centrality can be in many cases unequal For example, the two sentences below are seman Gehrmann et al., 2018) have achieved promising results thanks to the availability of large-

ing results thanks to the availability of large-scale datasets containing hundreds of thousands of the document-summary pairs (Sandhaus, 2008; Her-mann et al., 2015b; Grusky et al., 2018). Neverthe-less, it is unrealistic to expect that large-scale and high-quality training data will be available or cretically related: Half of hospitals are letting patients jump NHS queues for cataract surgery if they pay for it themselves, an investigation has revealed (2) Clara Eaglen, from the royal national in-

ated for different summarization styles (e.g., high

lights vs. single-sentence summaries), domains (e.g., user- vs. professionally-written articles), and

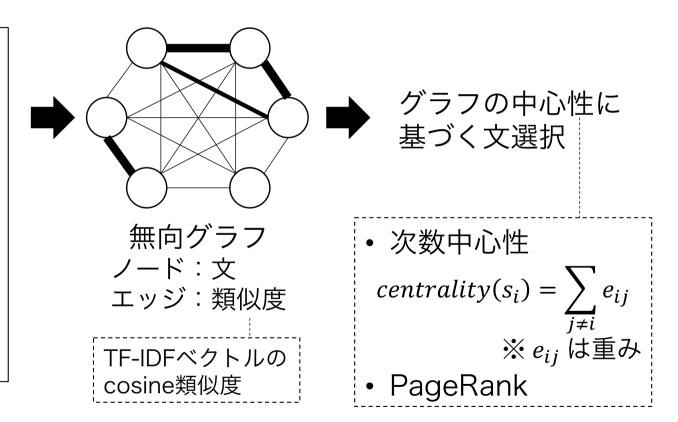
It therefore comes as no surprise that unsure

vised approaches have been the subject of much previous research (Marcu, 1997; Radev et al., 2000; Lin and Hovy, 2002; Mihalcea and Tarau,

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PACSUM:文間類似度

- ・BERT を fine-tuning
 - 仮説「ある文の前後の文は関連が強い」
 - 目的関数:

 $\frac{\log \sigma (v_{s_{i-1}}^T v_{s_i}) + \log \sigma (v_{s_{i+1}}^T v_{s_i}) + \mathbb{E}_s [\log \sigma (-v_s^T v_{s_i})]}{\text{前後の文とは近いベクトルに}}$ 他の文とは遠いベクトルに

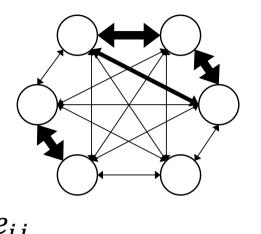
- 文間類似度
 - 類似度: $\overline{E}_{ij} = v_i^T v_j$
 - 正規化: $\tilde{E}_{ij} = \bar{E}_{ij} [\min \bar{E} + \beta (\max \bar{E} \min \bar{E})]$
 - 枝刈り: $E_{ij} = \begin{cases} \tilde{E}_{ij} & \text{if } \tilde{E}_{ij} > 0\\ 0 & \text{otherwise} \end{cases}$
 - β ∈ [0,1] が枝刈りのパラメタ

高すぎる値を補正

(正規化ではない)

PACSUM:有向グラフにおける中心性

- 有向性: 文の相対的な前後関係
 - ・無向エッジ → 双方向エッジ
- 入次数と出次数を区別した中心性

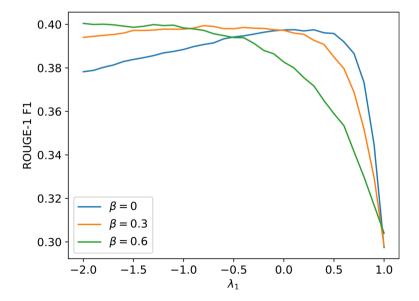


$$centrality(s_i) = \lambda_1 \sum_{j < i} e_{ij} + \lambda_2 \sum_{i < j} e_{ij}$$

前方の文(入次数)

後方の文(出次数)

- $\lambda_1 + \lambda_2 = 1$
 - λ₁, λ₂:重要度パラメタ
 - • λ_1 は負値になりがち(右図)
 - 前の文との類似度は
 文書要約にネガティブ効果



実験:教師ありモデルに匹敵 ※ ORACLE: 最良のROUGE-?をなる文選択要約

	INE	w York Limes		CNN/DailyMail				
	Method		NYT			CNN+DM		
	Method	R-1	R-2	R-L	R-1	R-2	R-L	
	Oracle	61.9	41.7	58.3	54.7	30.4	50.8	
教師あり	REFRESH ⁴ (Narayan et al., 2018b)	41.3	22.0	37.8	41.3	18.4	37.5	
	POINTER-GENERATOR (See et al., 2017)	42.7	22.1	38.0	39.5	17.3	36.4	
教師なし	LEAD-3	35.5	17.2	32.0	40.5	17.7	36.7	
	DEGREE (tf-idf)	33.2	13.1	29.0	33.0	11.7	29.5	
	TEXTRANK (tf-idf)	33.2	13.1	29.0	33.2	11.8	29.6	
	TEXTRANK (skip-thought vectors)	30.1	9.6	26.1	31.4	10.2	28.2	
	TEXTRANK (BERT)	29.7	9.0	25.3	30.8	9.6	27.4	
提案手法	PACSUM (tf-idf)	40.4	20.6	36.4	39.2	16.3	35.3	
	PACSUM (skip-thought vectors)	38.3	18.8	34.5	38.6	16.1	34.9	
	PACSUM (BERT)	41.4	21.7	37.5	40.7	17.8	36.9	

Now Varie Timese CNINI/Daily/Adi

評価指標:ROUGE (1, 2, L)

- 教師なし学習で PacSum が最も高性能
- ・
 文表現をBERTにしたことで性能向上

実験:中国語のニュース要約

Method	TTNews				
wiethou	R-1	R-2	R-L		
Oracle	45.6	31.4	41.7		
POINTER-GENERATOR	42.7	27.5	36.2		
LEAD	30.8	18.4	24.9		
TEXTRANK (tf-idf)	25.6	13.1	19.7		
PACSUM (BERT)	32.8	18.9	26.1		

- ・英語のデータセットより正解要約が abstractive
 - Pointer-Generator が非常に良い
 - Pointer-Generator : abstractive method
 - その他 : extractive method
- リード法/TextRankよりは良い

出力結果例 (NYT)

GOLD

Marine Corps says that V-22 Osprey, hybrid aircraft with troubled past, will be sent to Iraq in September, where it will see combat for first time.

The Pentagon has placed so many restrictions on how it can be used in combat that plane – which is able to drop troops into battle like helicopter and then speed away like airplane – could have difficulty fulfilling marines longstanding mission for it.

Limitations on v-22, which cost \$80 million apiece, mean it can not evade enemy fire with same maneuvers and sharp turns used by helicopter pilots.

PacSum

The Marine Corps said yesterday that the V-22 Osprey, a hybrid aircraft with a troubled past, will be sent to Iraq this September, where it will see combat for the first time.

The Pentagon has placed so many restrictions on how it can be used in combat that the plane — which is able to drop troops into battle like a helicopter and then speed away from danger like an airplane — could have difficulty fulfilling the Marines' longstanding mission for it.

The limitations on the V-22, which cost \$80 million apiece, mean it cannot evade enemy fire with the same maneuvers and sharp turns used by helicopter pilots.

∧

LEAD-3

the Marine Corps said yesterday that the V-22 Osprey, a hybrid aircraft with a troubled past, will be sent to Iraq this September, where it will see combat for the first time.

But because of a checkered safety record in test flights, the v-22 will be kept on a short leash.

The Pentagon has placed so many restrictions on how it can be used in combat that the plane – which is able to drop troops into battle like a helicopter and then speed away from danger like an airplane – could have difficulty fulfilling the marines ' longstanding mission for it.

細かい言い回し以外はほぼ同じ

提案手法は二文目を除外

人力評価:QA方式

NYT Method **CNN+DM TTNews** ORACLE 49.0^{*} 53.9* 60.0* REFRESH 42.5 34.2 34.7^{*} 26.0^{*} 50.0* LEAD PACSUM 44.4 56.0 31.1

- やり方
 - 正解要約から質問を作成
 - 質問:最重要コンテンツを答える質問
 - 要約を見て人が回答
 - 十分な情報を含む要約が有用
 - 正答率で評価(100点満点)
 - 部分正解:半分のスコア
- •結果(右上図)
 - そもそもORAGLEが良くない → 文選択の限界
 - 提案手法
 - ・他手法より良い
 → 改善の余地あり
 - ORACLEには劣る

まとめ

- 教師なし文書要約手法: PACSUM
 (Position-Augmented Centrality based Summarization)
 - Centrality-based Summarization
 - ➢ BERTに基づく文間類似度
 - ▶ 有向グラフ: 文の(相対的な)出現位置を考慮
- 実験
 - ▶ 教師ありモデルに匹敵する性能
 - ▶ 教師なしモデルでは最良
 - ORACLEには及ばない → 改善の余地あり
- なお、この論文の要約は提案手法で作られていない