

# Towards Context-free Information Importance Estimation




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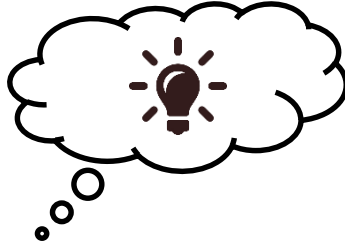
Markus Zopf

[zopf@aiphes.tu-darmstadt.de](mailto:zopf@aiphes.tu-darmstadt.de)

<https://www.aiphes.tu-darmstadt.de>

**Imp**(**i**, )



  
**Imp**(**i**)

# Automatic Information Importance Estimation



Need for Automatic  
Information Importance  
Estimation (IIE)



Information Overload



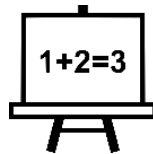
Importance of Information

# Towards Context-free Information Importance Estimation

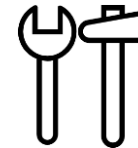
## On the Importance of Information



**A Definition  
of Importance**



**Evaluating  
IIE Abilities**



**The Need for  
Context-free IIE**

## Machine Learning for Context-free Information Importance Estimation



**Data**



**Machine  
Learning**



**Evaluation**

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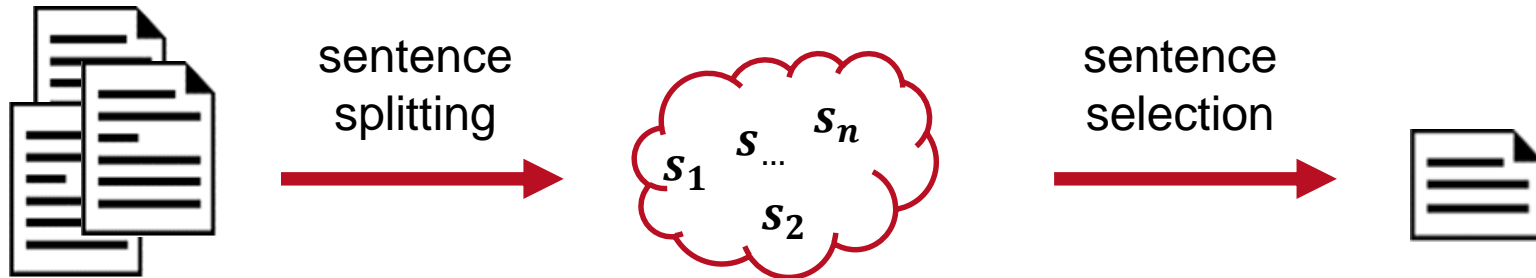
**Evaluation**



# (Extractive) Summarization



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1. make it shorter:  $|\text{output}| < \sum_{i=1}^n |\text{input}_i|$
2. don't add content:  $c(\text{output}) \subseteq \bigcup_{i=1}^n c(\text{input}_i)$ ,  $c : \text{Text} \rightarrow \text{Content}$
3. maximize a utility:  $\text{output}^* = \underset{\text{output} \in \text{Text}}{\operatorname{argmax}} u(c(\text{output}))$



# Definitions of Summarization



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source	major parts / important information
Wikipedia	✓
Oxford Dictionaries	✓
[Cleveland et al., 2013]	✓
[Spärck Jones, 1999]	✓
[Radev, et al., 2002]	✓
[Hovy, 2005]	
[Torres-Moreno, 2014]	✓
[Saggion et al., 2002]	
[Mani, 2001]	✓

**But: Which information is important?**



# Prior Methods for Information Value Estimation



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Shannon Information

$$\text{Inf}_{\text{Sh}}(w_i) = -\log(\text{Pr}(w_i))$$



Kolmogorov Complexity

$\text{Inf}_{\text{Ko}}(s)$  = “length of shortest  
algorithm to compute  $s$ ”

„I give a talk today“ vs. „Ffps gkw bci flvmnd eit“



# Definition: Information = Data + Meaning



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Luciano Floridi  
“Philosophy of Information”

*“The element  $i$  is an instance of information, understood as semantic concept, if and only if*

1.  *$i$  consists of  $n$  data with  $n \geq 1$ ,*
2. *the data are well-formed, and*
3. *the well-formed data are **meaningful**”*

meaningful data  $\approx$  data that can be interpreted/understood

„I give a talk today“ vs. „Ffps gkw bci flvmnd eit“

[Bar-Hillel & Carnap, 1953; Floridi, 2010]





# Amount of Semantic Information



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Semantic Information

$$\text{Inf}_{\text{Sem}}(i) = |S| - |S_i|$$

- system  $S$
- $S$  = prior knowledge about  $S$
- $S_i$  = knowledge about  $S$  after consuming information  $i$

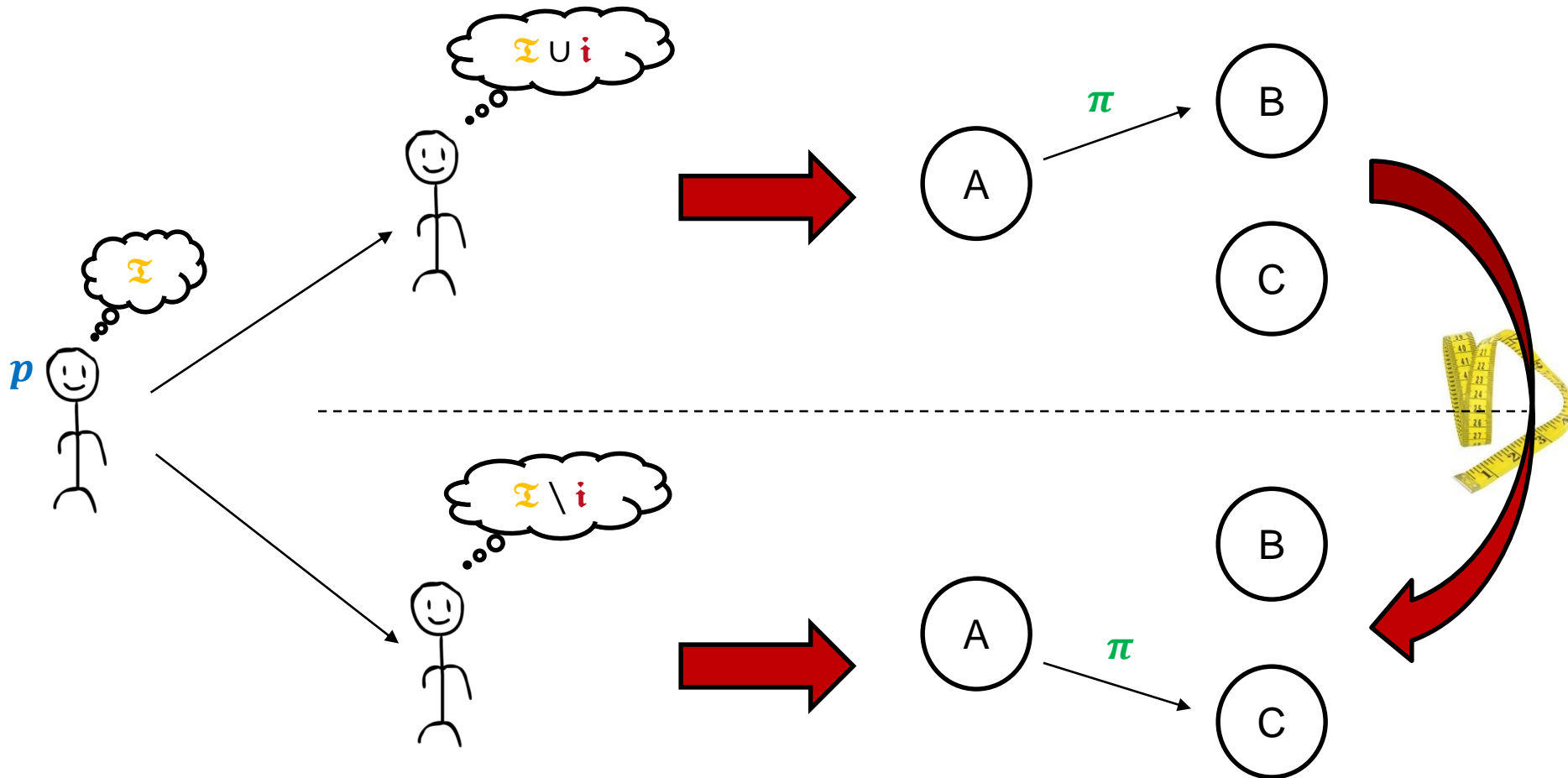
[Floridi, 2010]



# A Definition for Information Importance



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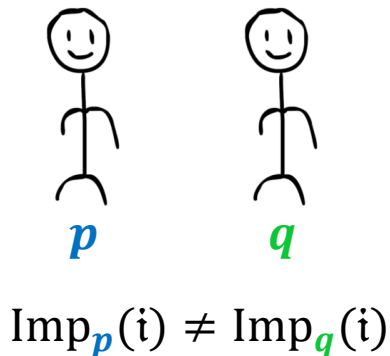
$$\text{Imp}_p(i) = d(\Pr(s|\pi_{\mathcal{I} \cup i}), \Pr(s|\pi_{\mathcal{I} \setminus i}))$$



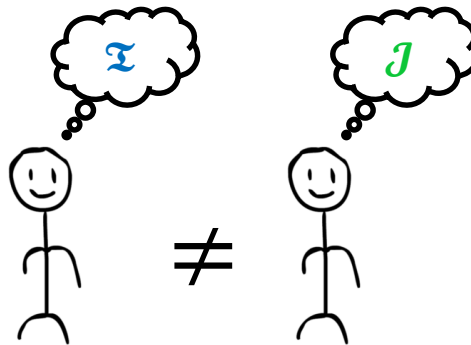
# Information Importance is...



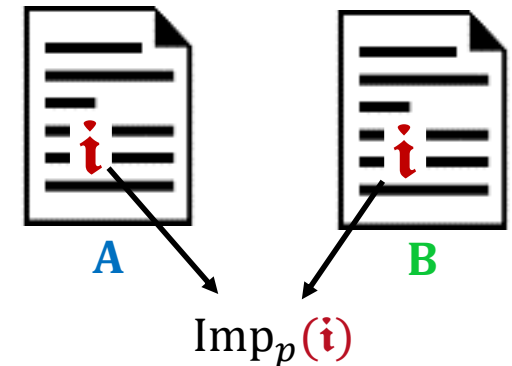
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**personalized:**  $\text{Imp}_p(i)$



**depends on prior  
knowledge**



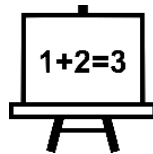
**invariant of the context  
it appears in:**  $\text{Imp}_p(i)$

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Evaluating  
IIE Abilities



The Need for  
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## Machine Learning for Context-free Information Importance Estimation



Data



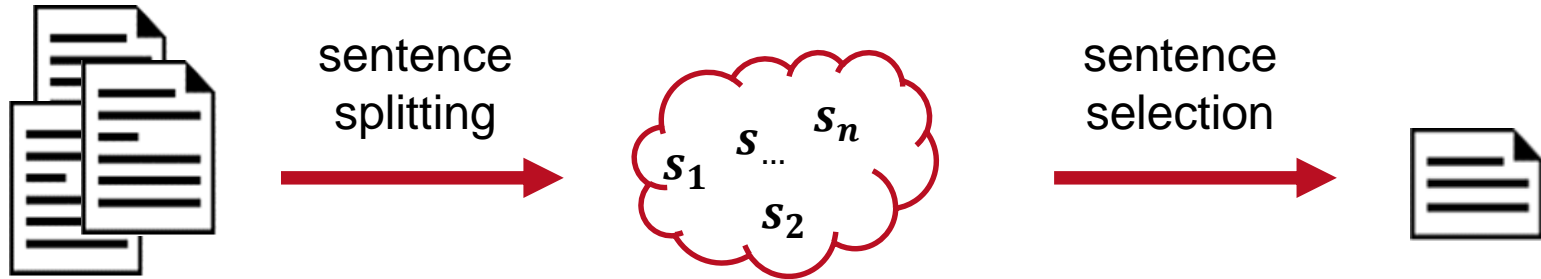
Machine  
Learning



Evaluation



# (Extractive) Summarization



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2. don't add content:  $c(\text{output}) \subseteq \bigcup_{i=1}^n c(\text{input}_i)$ ,  $c : \text{Text} \rightarrow \text{Content}$
3. maximize a utility:  $\text{output}^* = \underset{\text{output} \in \text{Text}}{\operatorname{argmax}} u(c(\text{output}))$

## Disadvantages

- redundancy avoidance + writing quality  $\rightarrow$  additional tasks to be solved jointly
- arbitrary length restrictions  $\rightarrow$  additional parameters/complexity
- only subset selection  $\rightarrow$  coarse-grained (binary) importance estimation



# Focus on Importance Estimation



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$$i_j > i_k$$

preference prediction  
for information nuggets

1.  $i_j$
2.  $i_k$
3.  $i_l$

information  
ranking

$$u(i_j)$$

utility  
prediction

[Zopf et. al, SNAMS 2018]

# Towards Context-free Information Importance Estimation

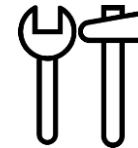
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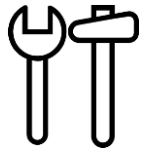
Data



Machine  
Learning



Evaluation



# Contextual Importance Estimation

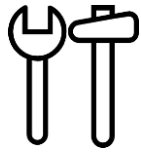


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**Contextual** Information  
Importance Estimation

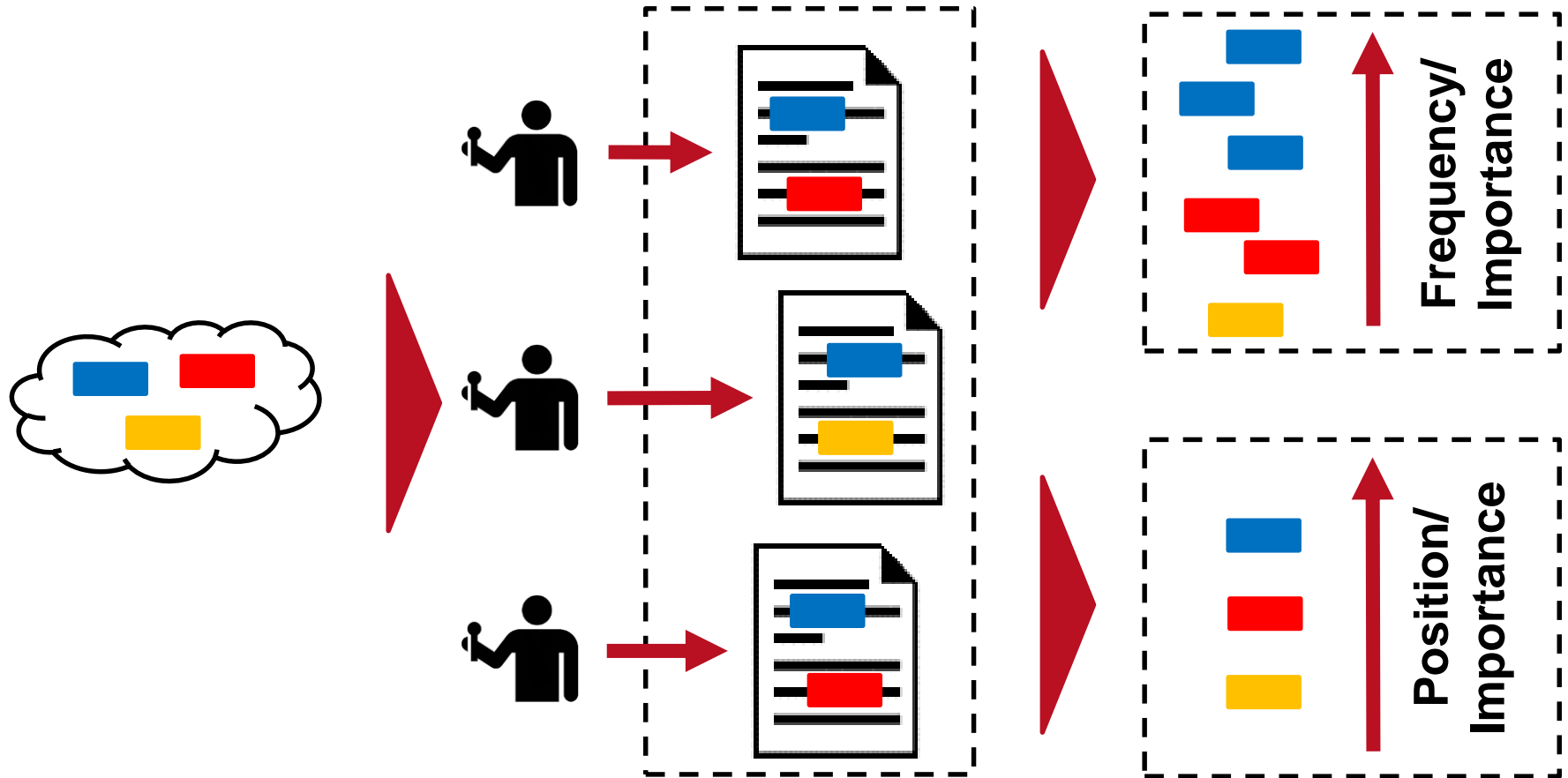


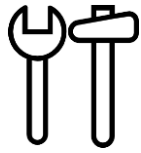


# Newswire Articles



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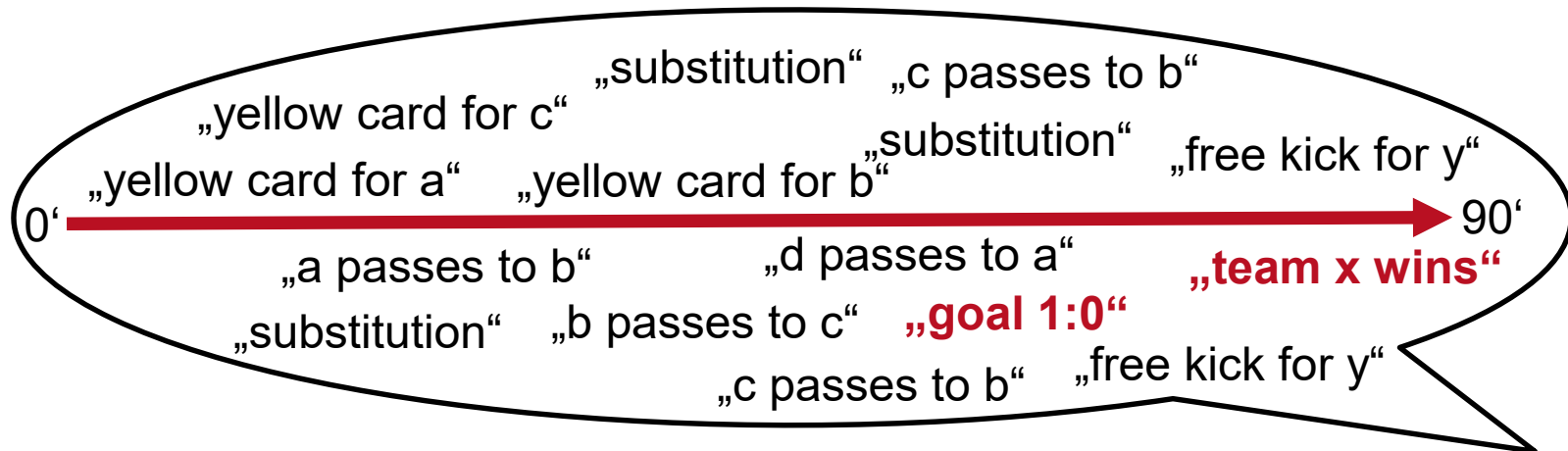




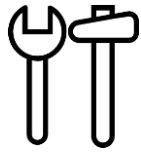
# Humans do not need document-derived features to estimate importance



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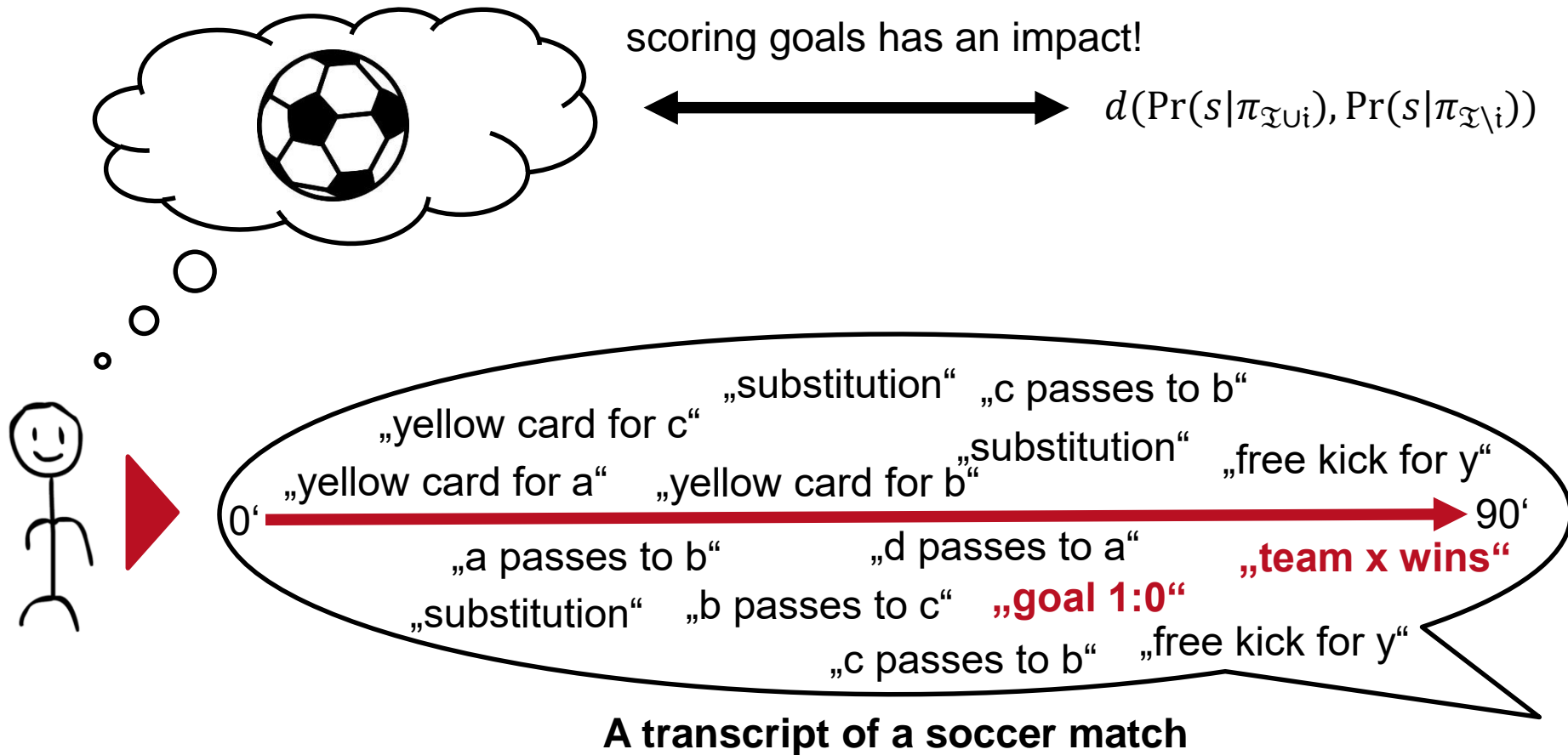
A transcript of a soccer match

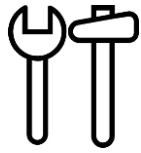


# Humans use prior domain knowledge for information importance estimation



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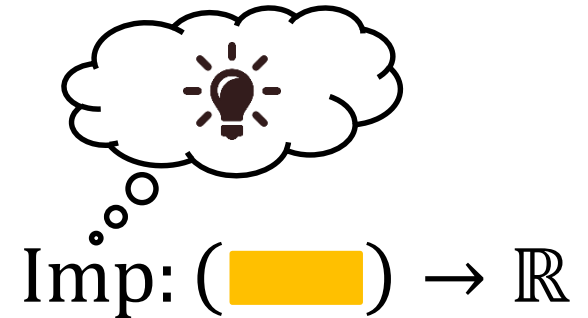
# Contextual Importance Estimation



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**Contextual** Information  
Importance Estimation



**Context-free** Information  
Importance Estimation

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Machine  
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Evaluation



# Creating multi-document summarization datasets is complex, tedious, and expensive



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search & read  
source documents



identify important  
information



write proper  
summaries

1. finding/reading source documents is **time consuming**
2. identifying important information requires **domain knowledge**
3. professional **writers** required to generate high quality

→ small multi-document summarization datasets





# A new Corpus Construction Approach



find texts which  
are summary



annotate all  
information nuggets



find source for each  
information nugget

[Zopf et al., COLING 2016]



# Wikipedia Provides Summaries



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Artikel Diskussion Lesen Quelltext bearbeiten Versionsgeschichte Wikipedia durchsuchen

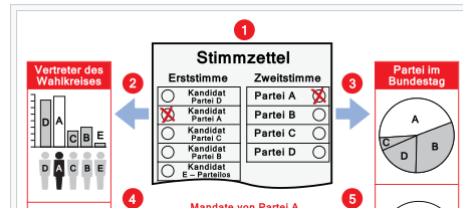
## Bundestagswahlrecht

Das **Bundestagswahlrecht** regelt die **Wahl** der **Mitglieder** des **Deutschen Bundestages**. Nach den in **Art. 38** Abs. 1 Satz 1 **Grundgesetz** (GG) festgelegten **Wahlrechtsgrundsätzen** ist die Wahl *allgemein, unmittelbar, frei, gleich und geheim*. Das konkrete **Wahlsystem** wird hingegen durch ein einfaches **Gesetz**, das **Bundeswahlgesetz**, bestimmt. Viele Bestimmungen des Bundeswahlgesetzes werden ihrerseits in der **Bundeswahlordnung** konkretisiert.

Typisch für das deutsche Bundestagswahlrecht ist die Verbindung von Wahlkreiswahl und Listenwahl. Ein Wähler hat zwei Stimmen, eine für einen Direktkandidaten im Wahlkreis und eine für die Landesliste einer Partei. Die Zweitstimme ist entscheidend für den Anteil einer Partei an den Bundestagsmandaten. Gewonnene Wahlkreismandate werden damit verrechnet.

### Inhaltsverzeichnis

- 1 Verfassungsrechtliche Grundlagen
- 2 Wahlrecht
  - 2.1 Aktives Wahlrecht
  - 2.2 Passives Wahlrecht
- 3 Wahlorgane



featured articles are

1. well-written
2. comprehensive
3. well-researched
4. neutral
5. stable

lead section

[Zopf et al., COLING 2016]





- **larger** than previous corpora
- **varying** number of source documents

corpus	# of topics	# of sources / topic $\pm$ sd
DUC 2004	50	10 $\pm$ 0.0
TAC 2008	48	10 $\pm$ 0.0
<b>hMDS</b>	<b>91</b>	<b>13.9 <math>\pm</math> 3.1</b>

- source documents from **many text genres**: articles, forum posts, microblogs, encyclopedic long and short, social media, scientific papers, dialogues
- contains topics in **English and German**
- [github.com/AIPHES/hMDS](https://github.com/AIPHES/hMDS)

[Zopf et al., COLING 2016]



## auto-*h*MDS



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- much larger

corpus	# of topics
DUC 2004	50
TAC 2008	48
<i>h</i> MDS	91
<b>auto-<i>h</i>MDS</b>	<b>7,316</b>

- **only \$0.07** per topic (for search engine)
- contains topics in **English and German**
- [github.com/AIPHES/auto-hMDS](https://github.com/AIPHES/auto-hMDS)

[Zopf, LREC 2018]

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## Machine Learning for Context-free Information Importance Estimation



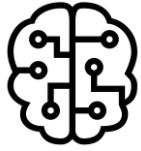
Data



Machine  
Learning



Evaluation



approximating unknown function  $f: \mathcal{X} \rightarrow \mathcal{Y}$

incidental supervision

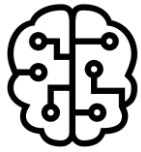
learn  $g \approx f$  without supervision

[Zopf et al., CoNLL 2016]

supervised learning (regression)

learn  $f$  from  $D = \{(x_1, y_1), \dots, (x_n, y_n)\}$

[Zopf et al., NAACL 2018]



# Incidental Supervision for Summarization



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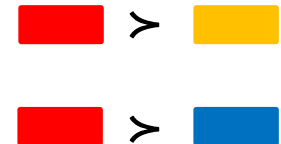
1. collect preferences:



document  $D_i$



summary  $R_i$



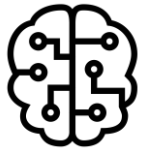
2. fit a Bradley-Terry model:

$$\Pr(e_i \succ e_j) = \frac{u(e_i)}{u(e_i) + u(e_j)}$$

3. estimate sentence utilities:

$$v(s) = \frac{1}{|s|} \sum_{e \in s} u(e) \quad \leftarrow \text{context-free}$$

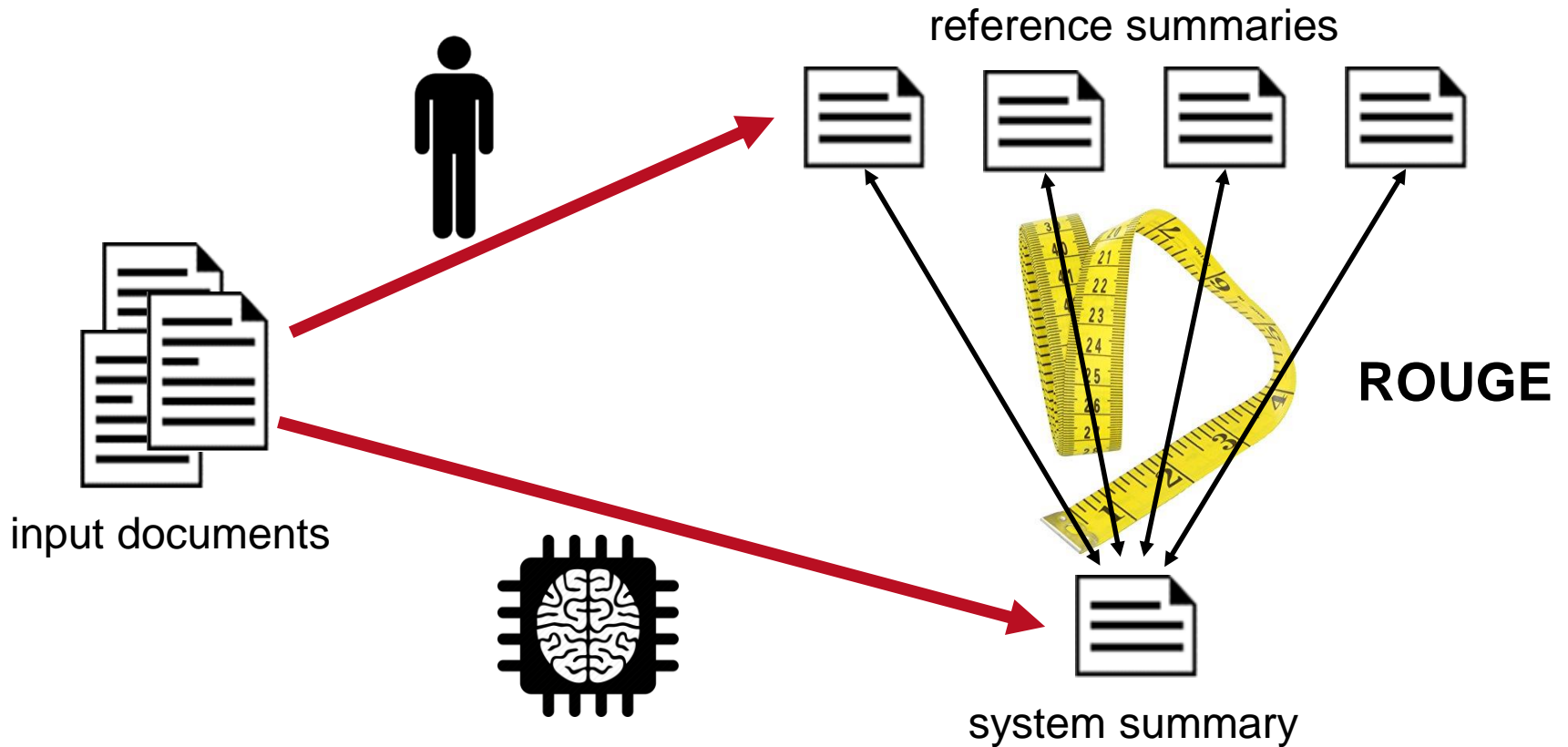
[Zopf et al., CoNLL 2016]



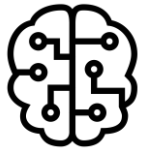
# ROUGE



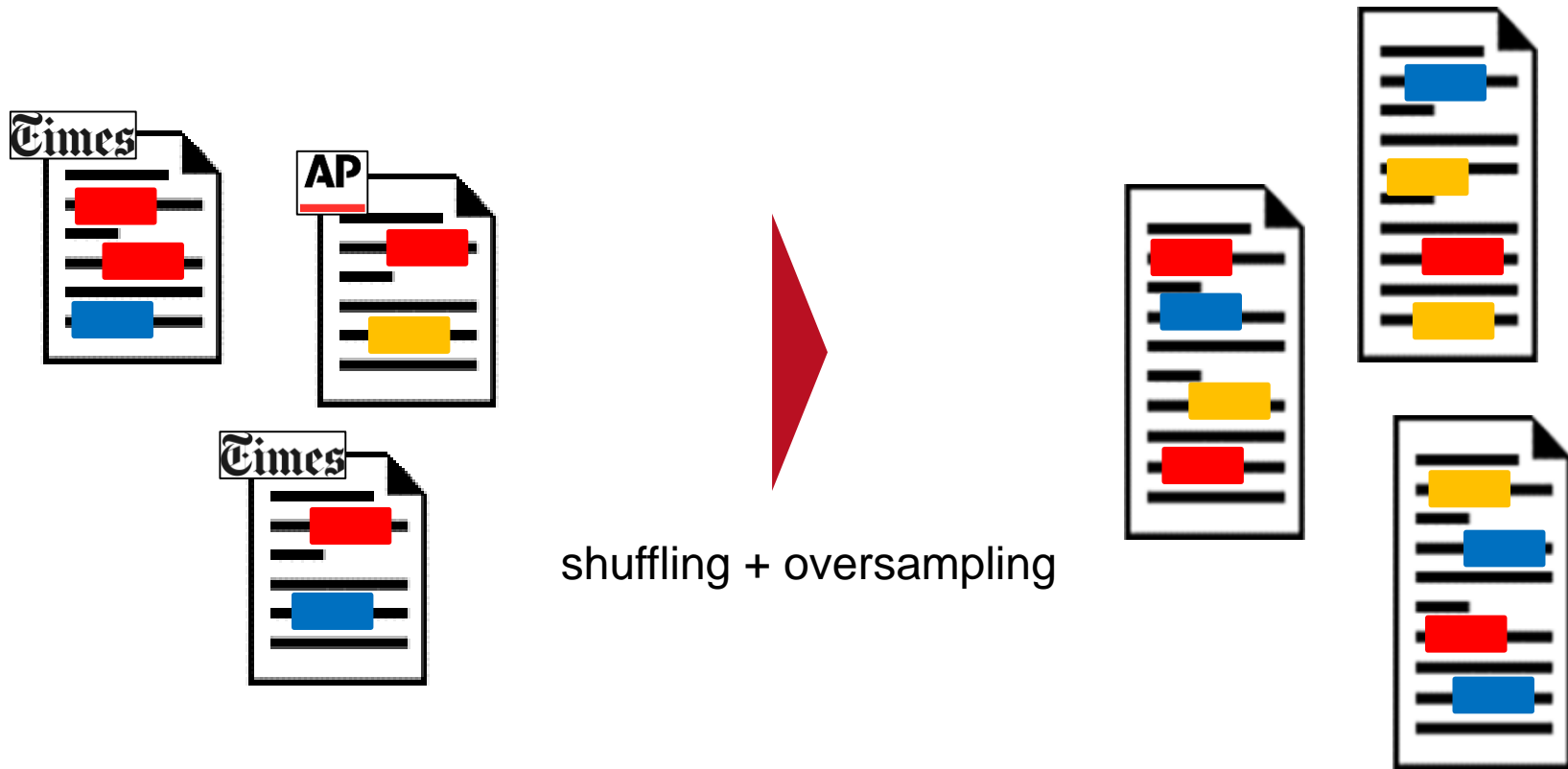
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[Zopf et al., CoNLL 2016]



# Shuffling and Oversampling



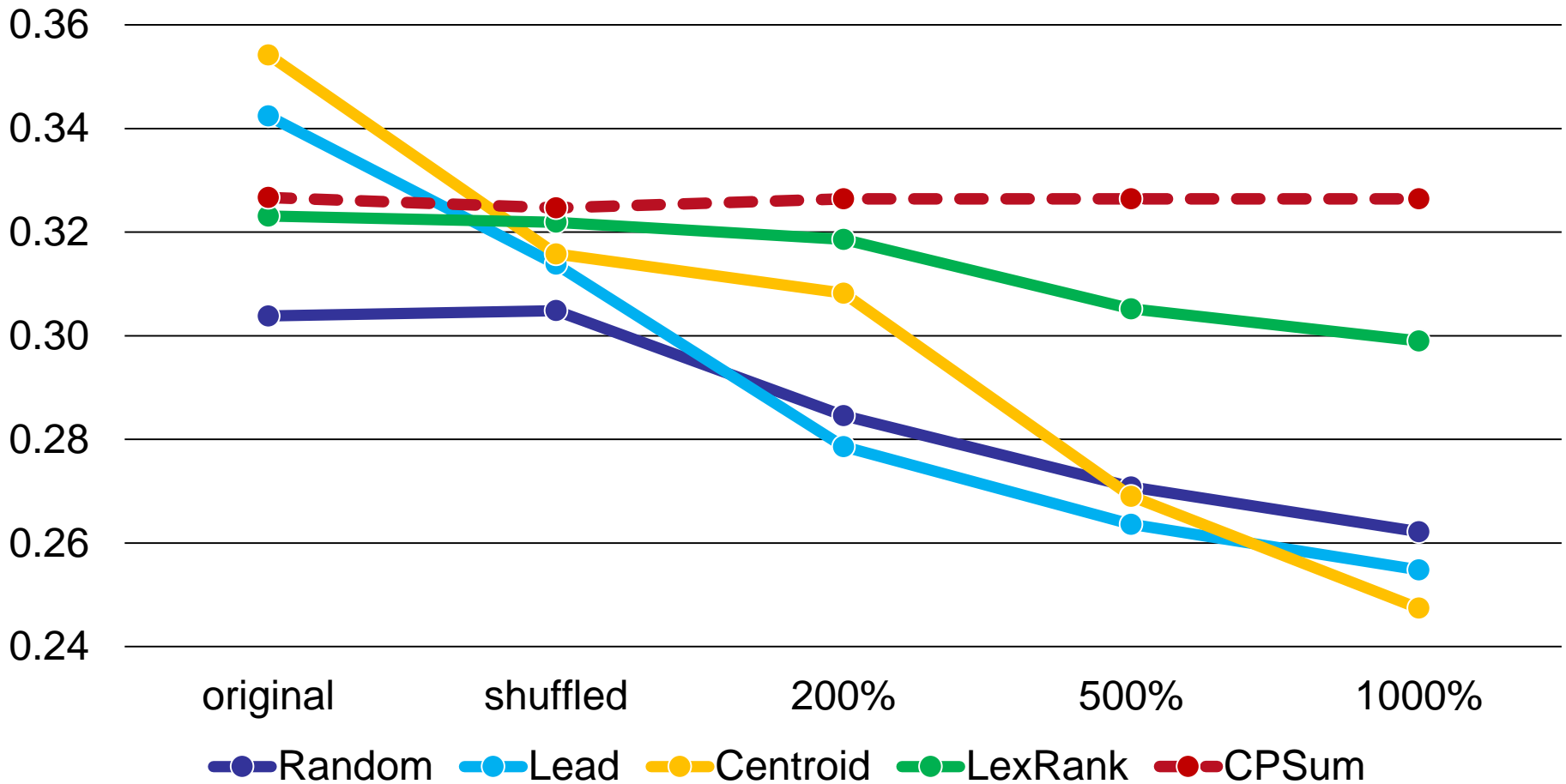
[Zopf et al., CoNLL 2016]



# ROUGE-1 scores for different versions of DUC 2004

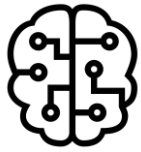


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[Zopf et al., CoNLL 2016]

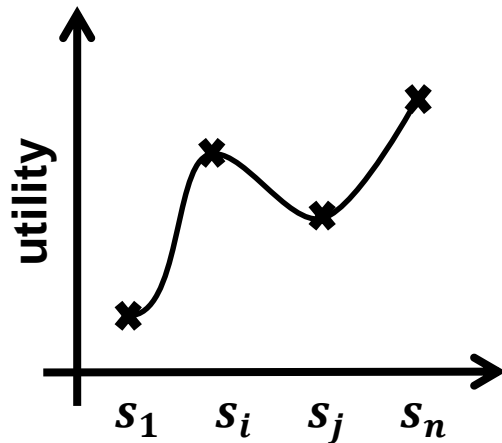




# Sentence regression for text summarization



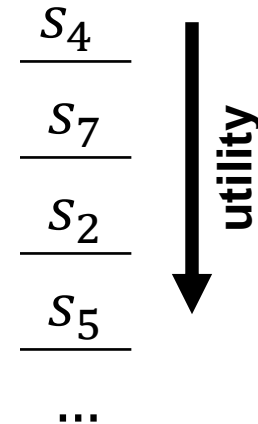
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$$f: \varphi(s) \rightarrow \mathbb{R}$$

sentence regression

+



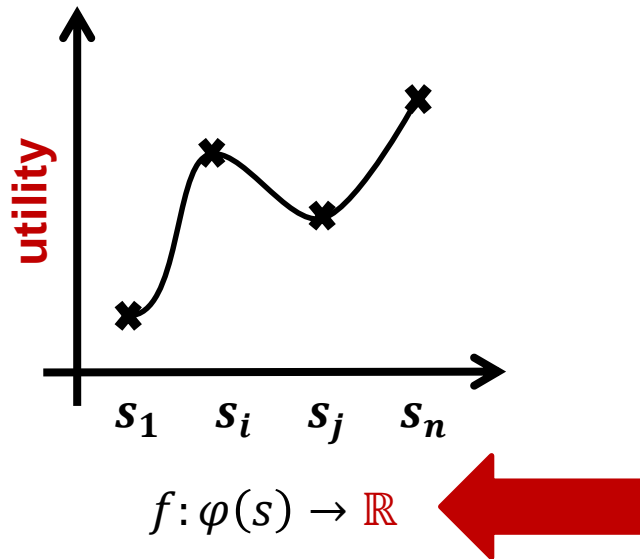
greedy sentence selection



# Sentence regression for text summarization

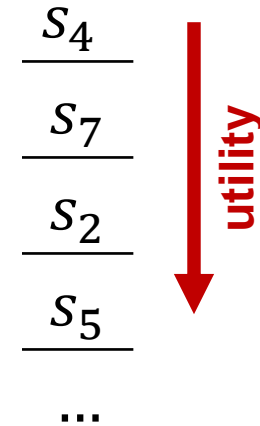


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sentence regression

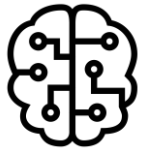
+



greedy sentence selection

not given in summarization datasets

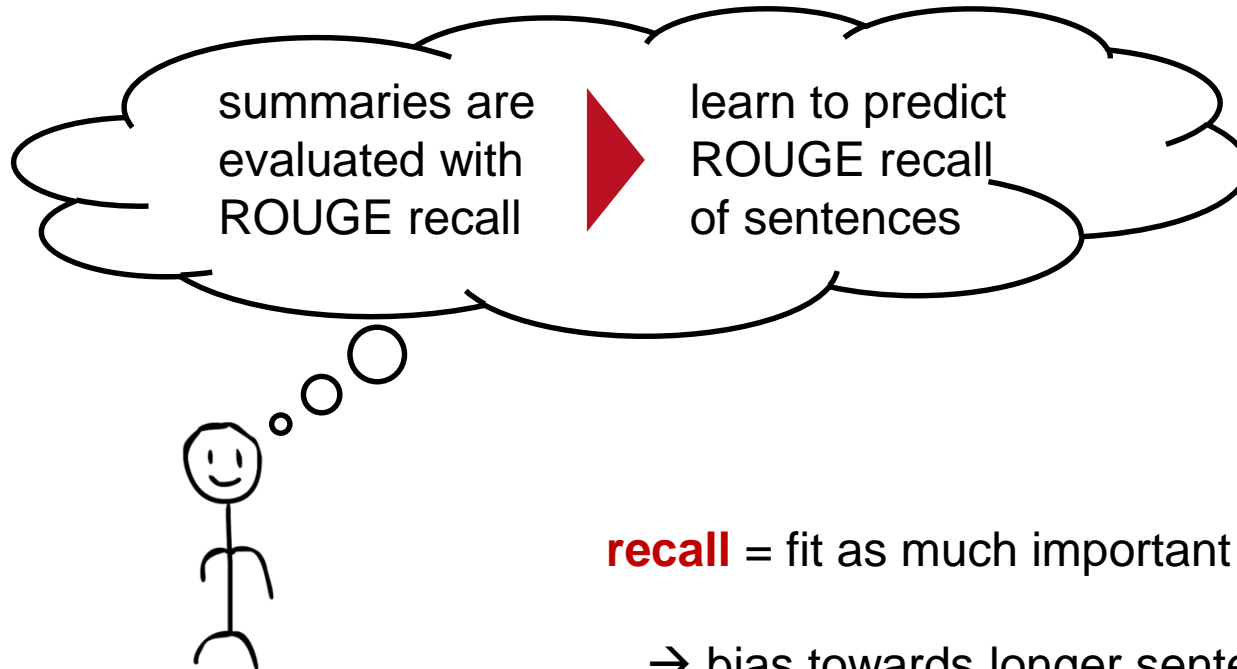




# Which regressand? ROUGE recall?



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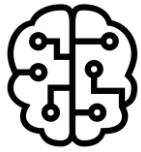
**recall** = fit as much important content as possible

→ bias towards longer sentences = wasting space



**precision** = waste as little space as possible

[Zopf et al., NAACL 2018]



# Sentence Length Experiments

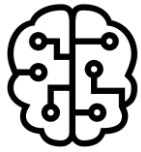


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regressand	avg. number of sentences		
	DUC 2004	TAC 2008	TAC 2009
random	6.66	5.21	4.89
max. ADW	6.56	5.06	5.11
avg. ADW	5.12	4.13	4.02
R1 Precision	7.76	6.75	6.07
R1 Recall	<b>3.42</b>	<b>2.67</b>	<b>2.70</b>
R2 Precision	7.10	6.13	6.09
R2 Recall	<b>4.26</b>	<b>3.46</b>	<b>3.55</b>

→ selecting according to recall leads to fewer (→ longer) sentences

[Zopf et al., NAACL 2018]



# Summarization Experiments

regressand	DUC 2004		TAC 2008		TAC 2009	
	R1	R2	R1	R2	R1	R2
random	0.3176	0.0466	0.2958	0.0460	0.2988	0.0463
max. ADW	0.3760	0.1013	0.4255	0.1546	0.3456	0.1105
avg. ADW	0.3850	0.0962	0.4097	0.1243	0.3548	0.0934
R1 Precision	<b>0.4129</b>	0.1118	<b>0.4356</b>	0.1465	<b>0.3945</b>	0.1217
R1 Recall	0.3863	0.0899	0.3928	0.1108	0.3431	0.0837
R2 Precision	0.3918	<b>0.1273</b>	0.4346	<b>0.1819</b>	0.3781	<b>0.1364</b>
R2 Recall	0.3923	0.1207	0.4239	0.1620	0.3742	0.1303

→ greedy selection according to precision leads to high recall in the end  
→ prior works predict suboptimal scores

[Zopf et al., NAACL 2018]

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# Creating reference summaries is expensive and similarity estimation is unreliable



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1. reference summaries have to be produced by humans



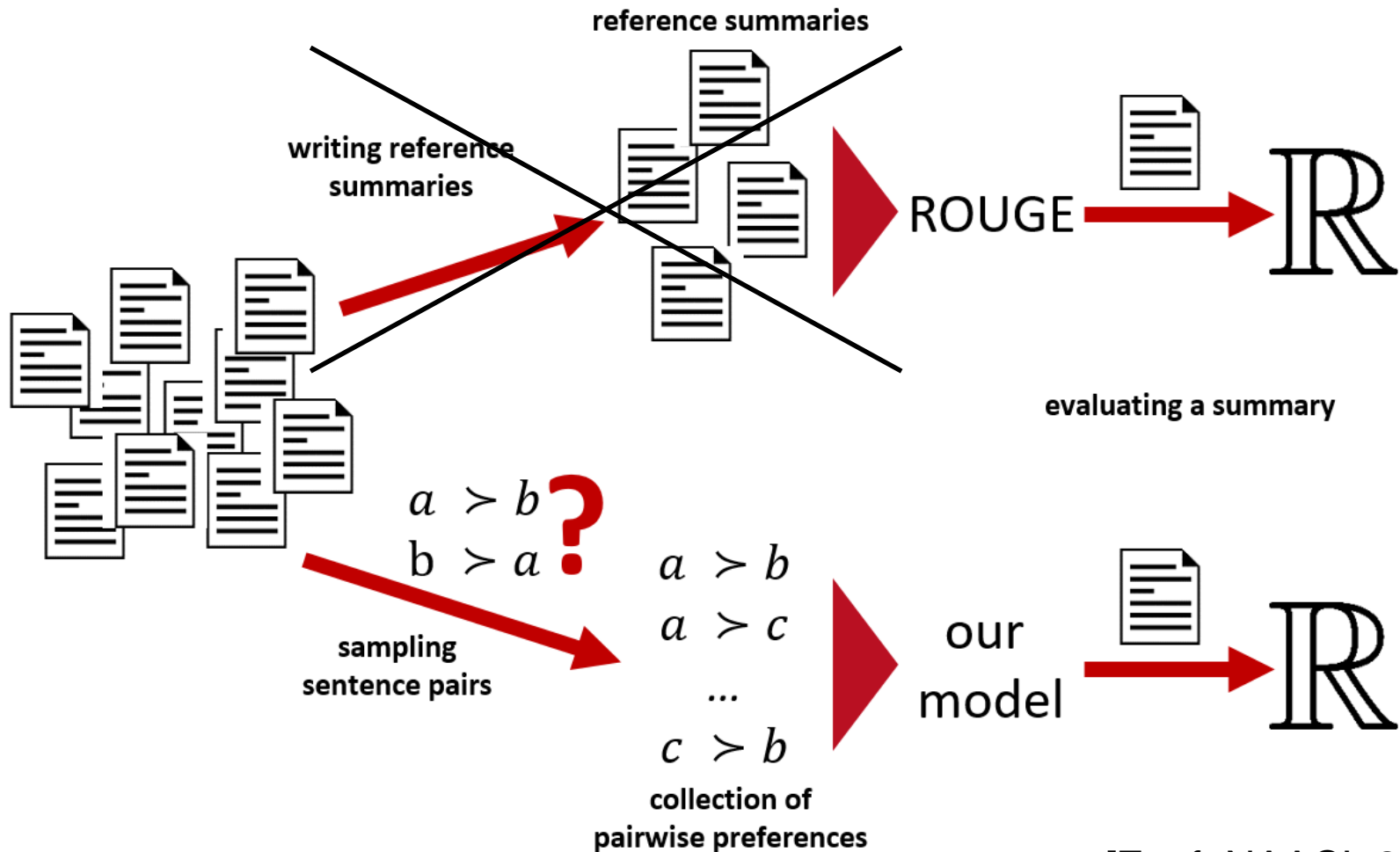
2. computing (semantic) similarity between texts is complex (unsolved problem)



# Pairwise preferences over sentences can be used instead



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[Zopf, NAACL 2018]

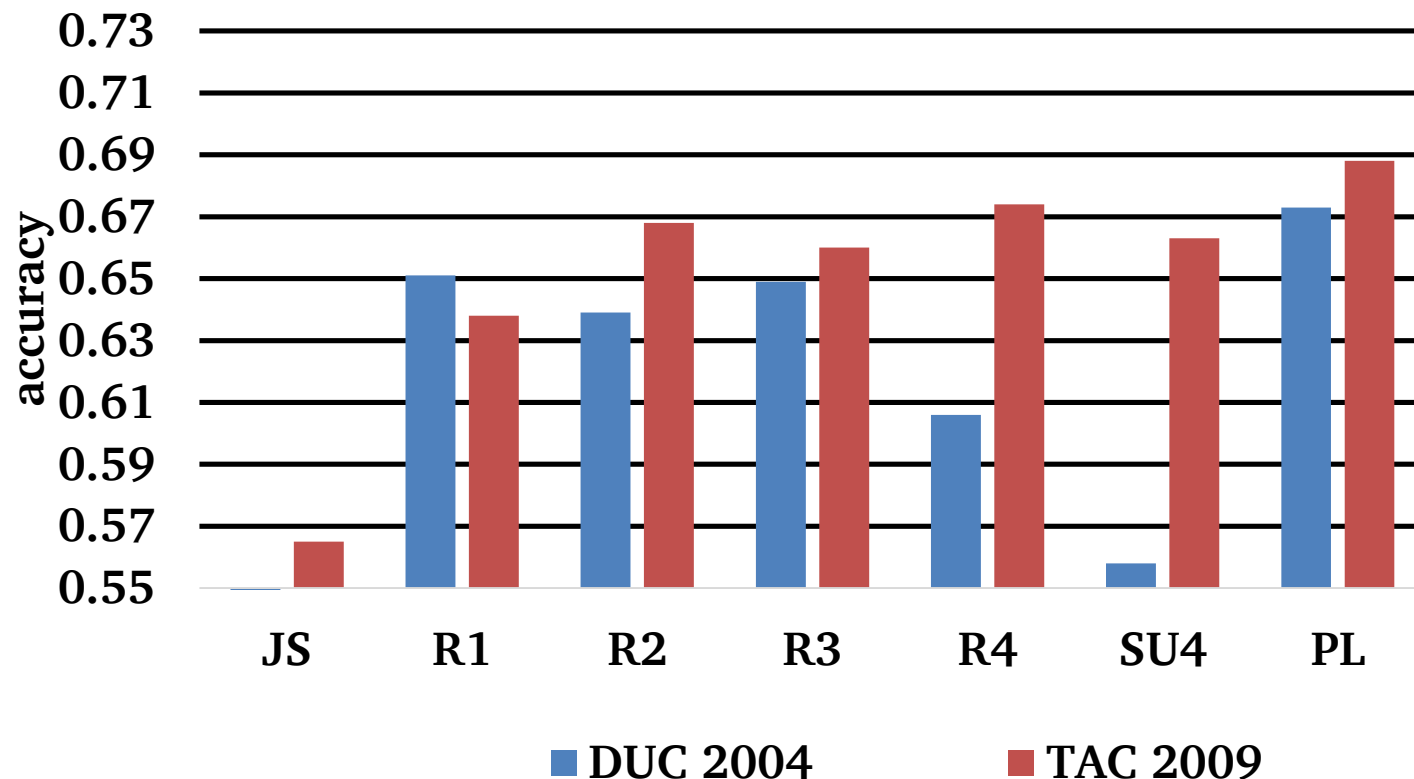




# Preference-based evaluation outperforms popular versions of ROUGE



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200 preferences per topic

→ ~54 minutes per topic

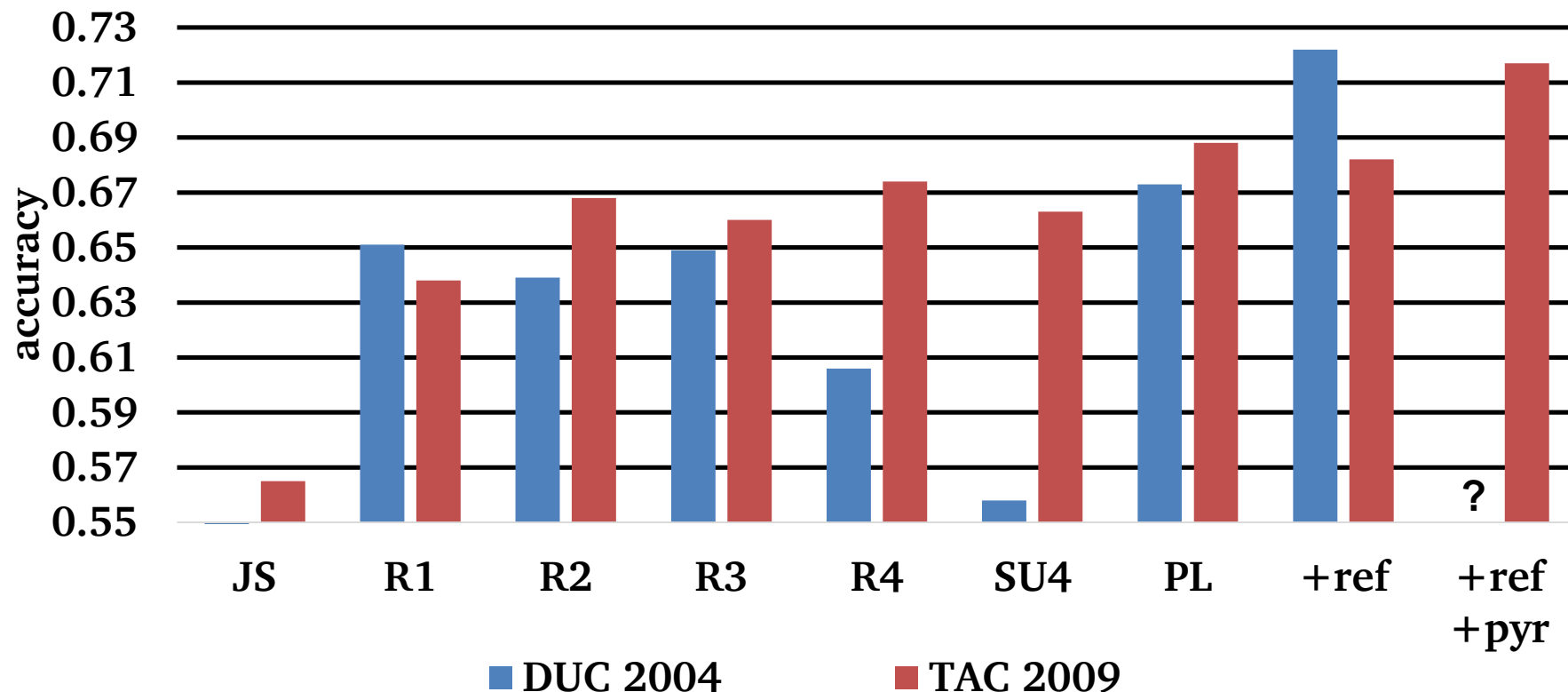
[Zopf, NAACL 2018]



# Automatically generated preferences can further improve performance



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+ref = automatic preferences based on reference summaries

+pyr = automatic preferences based on Pyramid scores

[Zopf, NAACL 2018]



# Summary: A Definition of Importance



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## Problems

- **vague intuition** of „importance“
  - leads to many discussions based on misunderstandings
- definition of importance only **by example**

## Contributions

- two **formal definitions** of information importance
  - common discussion ground
- analysis of **implications**

## Future Work

- develop more definitions and compare implications



# Summary: Evaluating IIE Abilities



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## Problems

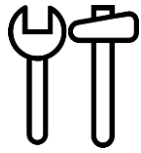
- summarization **suboptimal** to investigate importance estimation

## Contributions

- motivation for importance estimation as **standalone research domain**
  - allows to focus on importance estimation
- three new tasks
  - pairwise **preference** prediction
  - **rankings** according to importance
  - **utility** prediction for information nuggets

## Future Work

- new datasets and systems for new tasks



# Summary: The Need for Context-free IIE



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## Problems

- summarization focuses mainly on **newswire documents**
  - special text genre with special properties
- correlation  $\neq$  causality
- correlation can be removed by shuffling / oversampling [Zopf et al., 2016]

## Contributions

- **analysis** why summarization systems work the way they do
- proposed **context-free** importance estimation instead



# Summary: Data



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## Problems

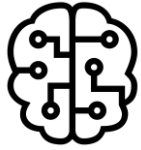
- no **heterogeneous** MDS datasets are available
- **large** MDS datasets are missing
  - construction is **too complex and expensive**
- large datasets required for training and testing

## Contributions

- novel **cost-effective** corpus construction **approach**
- validated applicability by producing **hMDS**
- extended idea to produce **auto-hMDS** fully automatically
  - **much larger** than prior MDS datasets

## Future Work

- human summarization experiments



# Summary: Machine Learning



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## Contributions

- first **context-free** information importance estimator  
→ more (incidental) training data can be used
- resolved a common **misconception** about regressands in sentence regression

## Future Work

- explore more context-free information importance estimators



# Summary: Evaluation



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## Problems

- evaluation requires **expensive** reference summaries
- based on rough approximation of **text similarities**

## Contributions

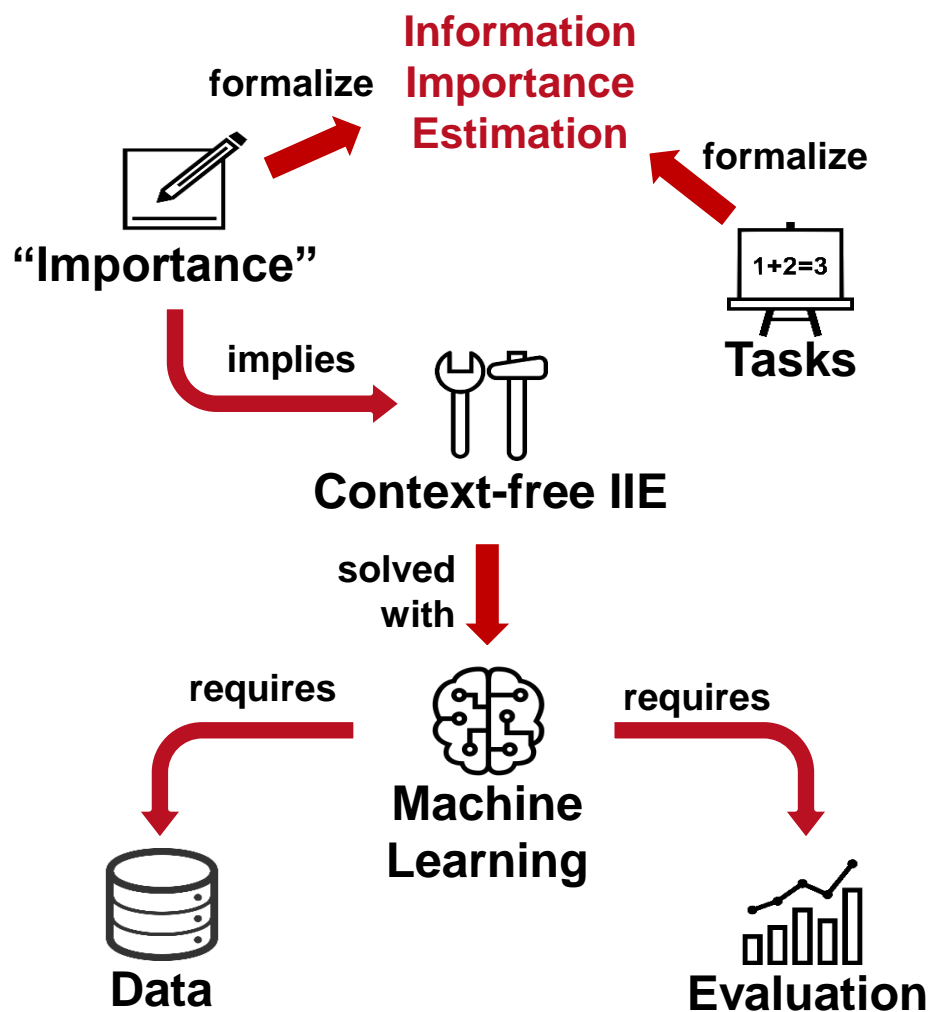
- a **new evaluation metric**
  - no reference summaries
  - no text-to-text semantic similarity estimation
- new metric performs better than different versions of ROUGE

## Future work

- evaluate on more (diverse) datasets



# Towards Context-free Information Importance Estimation



- **Markus Zopf**, et al. What's Important in a Text? An Extensive Evaluation of Linguistic Annotations for Summarization. SNAMS 2018, pp. 272–277
- **Markus Zopf**. Estimating Summary Quality with Pairwise Preferences. NAACL 2018, pp. 1687–1696
- **Markus Zopf**, Eneldo Loza Mencía, and Johannes Fürnkranz. Which Scores to Predict in Sentence Regression for Text Summarization? NAACL 2018, pp. 1782–1791
- **Markus Zopf**. auto-hMDS: Automatic Construction of a Large Heterogeneous Multi-Document Summarization Corpus. LREC 2018, pp. 3228–3233
- **Markus Zopf**, Maxime Peyrard, and Judith Eckle-Kohler. The Next Step for Multi-Document Summarization : A Heterogeneous Multi-Genre Corpus Built with a Novel Construction Approach. COLING 2016, pp. 1535–1545
- **Markus Zopf**, Eneldo Loza Mencía, and Johannes Fürnkranz. Sequential Clustering and Contextual Importance Measures for Incremental Update Summarization. COLING 2016, pp. 1071–1082
- **Markus Zopf**, Eneldo Loza Mencía, and Johannes Fürnkranz. Beyond Centrality and Structural Features: Learning Information Importance for Text Summarization. CoNLL 2016, pp. 84–94
- **Markus Zopf**. SeqCluSum: Combining Sequential Clustering and Contextual Importance Measuring to Summarize Developing Events over Time. TREC 2015