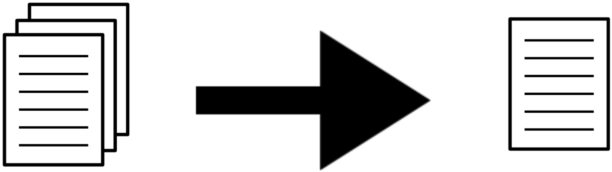
Automatic Detection of Linguistic Quality Violations

Jonathan Oberländer

Bachelor Thesis Defense
Universität des Saarlandes
21.08.2014

Automatic Summarization



Automatic Summarization

- **Single-Document:** One document
- **Multi-Document:** Multiple documents on the same topic

Automatic Summarization

- **Single-Document:** One document
- **Multi-Document:** Multiple documents on the same topic

- **Abstractive:** Internal semantic representation + generation
- **Extractive:** New summary from source sentences

Automatic Summarization

- **Single-Document:** One document
- **Multi-Document:** Multiple documents on the same topic

- **Abstractive:** Internal semantic representation + generation
- **Extractive:** New summary from source sentences

	Single-document	Multi-document
Abstractive		
Extractive		

Linguistic Quality Violations

Summarization systems should produce coherent and grammatical output.

Linguistic Quality Violations

Summarization systems don't produce coherent and grammatical output.
Why?

- It's hard.

Linguistic Quality Violations

Summarization systems don't produce coherent and grammatical output.
Why?

- It's hard.
- Evaluation: content, information density

Linguistic Quality Violations

Summarization systems don't produce coherent and grammatical output.
Why?

- It's hard.
- Evaluation: content, information density

$\Rightarrow$ LQVSumm (Friedrich et al., 2014)

LQVSumm (Friedrich et al., 2014)

Annotated results of TAC 2011 Guided Summarization task (Owczarzak and Dang, 2011)

LQVSumm (Friedrich et al., 2014)

Annotated results of TAC 2011 Guided Summarization task (Owczarzak and Dang, 2011)

- Entity level:
  - definite noun phrase without reference to previous mention
  - pronoun with missing antecedent
  - acronym without explanations
  - ...

LQVSumm (Friedrich et al., 2014)

Annotated results of TAC 2011 Guided Summarization task (Owczarzak and Dang, 2011)

- Entity level:
  - definite noun phrase without reference to previous mention
  - pronoun with missing antecedent
  - acronym without explanations
  - ...
- Clause level:
  - **incomplete sentence (INCOMPLSN)**
  - **inclusion of datelines (INCLDATE)**
  - **other ungrammatical form (OTHRUNGR)**
  - no semantic relatedness (NOSEMREL)
  - **redundant information (REDUNINF)**
  - no discourse relation (NODISREL)

LQVSumm (Friedrich et al., 2014)

- small
- partially inconsistent

LQVSumm (Friedrich et al., 2014)

- small
- partially inconsistent
- corpus preprocessing with CoreNLP (Manning et al., 2014)
- unit of annotation (clauses vs. sentences)

LQVSumm (Friedrich et al., 2014)

- small
- partially inconsistent
- corpus preprocessing with CoreNLP (Manning et al., 2014)
- unit of annotation (clauses vs. sentences)
- OTHRUNGR has different violation subtypes

Development and Test Sets

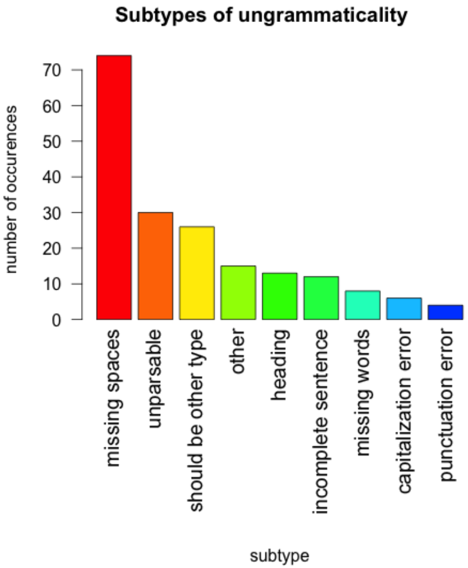
2 development sets:

- *dev-1*: 20% (D1101-D1108)
- *dev-2*: 20% (D1109-D1116)

1 test set:

- *test*: 60% (D1117-D1144)

Ungrammaticality (OTHRUNGR+INCOMPLSN) on *dev-2*



Detecting missing spaces

"A strong earthquake measuring 7.8 magnitude struck **Wenchuancounty** *of Sichuan Province on Monday, leaving at least* **12,000people** *died and thousands more injured."*

"Virginia Tech reported a campus shooting Monday and told **studentsto** *stay inside their residences and away from windows."*

"A gunman opened fire on classrooms at Virginia Tech University **onMonday** *morning, killing at least 30 people before turning his* **gunon** *himself in the bloodiest school shooting in US history."*

Unknown Tokens

Idea:
Sentence contains violation iff any word $\notin$ known tokens

UnknownTokens

Idea:
Sentence contains violation iff any word $\notin$ known tokens

known tokens?

- Source documents available? $\rightarrow$ all tokens in source documents = **UnknownTokens-source**
- Otherwise $\rightarrow$ **UnknownTokens-general**

UnknownTokens-general

- Tokens from (parts of) Gigaword = **UnknownTokens-gw**

UnknownTokens-general

- Tokens from (parts of) Gigaword = **UnknownTokens-gw**
- + Heuristics (Capitalized words) = **UnknownTokens-gw+heur**

UnknownTokens-general

- Tokens from (parts of) Gigaword = **UnknownTokens-gw**
- + Heuristics (Capitalized words) = **UnknownTokens-gw+heur**
- + NER (Finkel et al., 2005) = **UnknownTokens-gw+heur+ner**

UnknownTokens-general

- Tokens from (parts of) Gigaword = **UnknownTokens-gw**
- + Heuristics (Capitalized words) = **UnknownTokens-gw+heur**
- + NER (Finkel et al., 2005) = **UnknownTokens-gw+heur+ner**
- + Wikipedia = **UnknownTokens-gw+heur+ner+wiki**

= **UnknownTokens-general**

UnknownTokens: Evaluation on *dev-2*

	Missing spaces		
	P	**R**	**F**
UT-source	95.9	94.6	95.2

UnknownTokens: Evaluation on *dev-2*

	Missing spaces		
	P	**R**	**F**
UT-source	95.9	94.6	95.2
UT-gw	15.0	**98.7**	26.0

UnknownTokens: Evaluation on *dev-2*

	Missing spaces		
	P	**R**	**F**
UT-source	95.9	94.6	95.2
UT-gw	15.0	**98.7**	26.0
UT-gw+heur	30.5	97.3	46.5

UnknownTokens: Evaluation on *dev-2*

	Missing spaces		
	P	**R**	**F**
UT-source	95.9	94.6	95.2
UT-gw	15.0	**98.7**	26.0
UT-gw+heur	30.5	97.3	46.5
UT-gw+heur+ner	35.5	97.3	52.0

UnknownTokens: Evaluation on *dev-2*

	Missing spaces		
	P	**R**	**F**
UT-source	95.9	94.6	95.2
UT-gw	15.0	**98.7**	26.0
UT-gw+heur	30.5	97.3	46.5
UT-gw+heur+ner	35.5	97.3	52.0
UT-gw+heur+ner+wiki	**70.3**	96.0	**81.2**

RandomForest

RandomForest (Breiman, 2001) to train decision trees

Features:

RandomForest

RandomForest (Breiman, 2001) to train decision trees

Features:

- classification from **UnknownTokens**

RandomForest

RandomForest (Breiman, 2001) to train decision trees

Features:

- classification from **UnknownTokens**
- perplexity scores from language model trained on Gigaword

RandomForest

RandomForest (Breiman, 2001) to train decision trees

Features:

- classification from **UnknownTokens**
- perplexity scores from language model trained on Gigaword
- number of words

RandomForest

RandomForest (Breiman, 2001) to train decision trees

Features:

- classification from **UnknownTokens**
- perplexity scores from language model trained on Gigaword
- number of words
- 3 features from ACE (Packart, 2011) output:
    - number of readings
    - RAM usage
    - status

RandomForest: Evaluation on *test*

	Precision	**Recall**	**F-Score**
Ungrammatical	72.8	49.1	58.6

RandomForest: Evaluation on *test*

	Precision	**Recall**	**F-Score**
Ungrammatical	72.8	49.1	58.6

Ablation Study:

Feature	Decrease in Accuracy
UnknownTokens Output	0.3369
Language Model Perplexity	1.2091
Number of Words	0.7334
ACE RAM	1.0901
ACE Readings	1.3478
ACE Status	0.1982

Datelines (INCLDATE)

BLACKSBURG, Virginia 2007-04-16 18:34: 44 UTC *A gunman opened fire in a dorm and classroom at Virginia Tech on Monday, killing at least 30 people in the deadliest shooting rampage in U.S. history.*

BERLIN, May 13(Xinhua) *The German government announced on Tuesday that it is to provide 500, 000 euros(around 770, 000 U.S. dollars) in aid for earthquake victims in Sichuan Province of China.*

00 a.m.*People are panicking.*

Detecting Datelines

Regular expression:

```
UTC|
^\d{4}-\d{2}-\d{2}|
^[A-Z]{3,}|
^(Jan|Feb|Mar|Apr|May|Jun|Jul|Aug|Sep|Oct|Nov|Dec)
```

Detecting Datelines

Regular expression:

```
UTC|
^\d{4}-\d{2}-\d{2}|
^[A-Z]{3,}|
^(Jan|Feb|Mar|Apr|May|Jun|Jul|Aug|Sep|Oct|Nov|Dec)
```

Evaluation on *test*:

Precision	Recall	F-Score
86.0%	89.7%	87.8%

Redundancy (REDUNINF)

According to a survey by the State **Food and Drug** *Administration, 65 percent of the respondents worried about the food* **safety** *situation in China.*

Food and drug safety *has become a major concern of Chinese people.*

Cyclone *Sidr, described as the worst storm in years to hit low-lying and disaster-prone* **Bangladesh***, crashed into the southwestern coast* **Thursday** *night* **before sweeping north** *over* **the capital Dhaka.**

The **cyclone** *hit the southwestern coast of* **Bangladesh** *on* **Thursday before sweeping north** *to* **the capital Dhaka.**

Unigrams

Mary saw the 5 “elephants”. She saw the horses.

Unigrams

$\{Mary, saw, the, 5, elephants\}, \{She, saw, the, horses\}$

- Remove non-alphanumeric characters and split into set of words

Unigrams

$$|\{saw, the\}| = 2$$

- Remove non-alphanumeric characters and split into set of words
- Cardinality of intersection between sets

Unigrams

$$score = \frac{2}{|\{She, saw, the, horses\}|} = 0.5$$

- Remove non-alphanumeric characters and split into set of words
- Cardinality of intersection between sets
- Normalize by sentence length

Unigrams

$$0.5 > \textit{threshold} \; ?$$

- Remove non-alphanumeric characters and split into set of words
- Cardinality of intersection between sets
- Normalize by sentence length
- Classify with threshold

Unigrams

$$0.5 > \mathit{threshold}\ ?$$

- Remove non-alphanumeric characters and split into set of words
- Cardinality of intersection between sets
- Normalize by sentence length
- Classify with threshold

Variations: **Bigrams**, **Combined**

Unigrams

$$0.5 > \mathit{threshold}\ ?$$

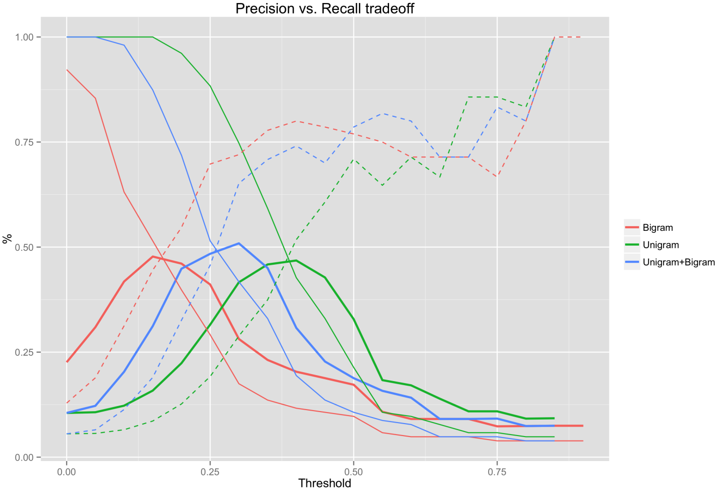
- Remove non-alphanumeric characters and split into set of words
- Cardinality of intersection between sets
- Normalize by sentence length
- Classify with threshold

Variations: **Bigrams**, **Combined**

Threshold?

Finding a threshold

dev-1+2



Evaluation of **Unigrams**, ... on *test*

	Unigrams	**Bigrams**	**Combined**
Threshold	0.5	0.4	0.4

	Precision	Recall	F-Score
Baseline	4.5%	**100%**	8.7%
Levenshtein	15.8%	17.3%	3.1%
Unigrams	**58.0%**	28.2%	**37.0%**
Bigrams	55.6%	14.5%	22.9%
Combined	56.8%	24.3%	34.0%

Conclusion

Best methods:

	Precision	Recall	F-Score
Ungrammaticality	72.8	49.1	58.6
Datelines	86.0	89.7	87.8
Redundancy	58.0	28.2	37.0

Conclusion

Best methods:

	Precision	Recall	F-Score
Ungrammaticality	72.8	49.1	58.6
Datelines	86.0	89.7	87.8
Redundancy	58.0	28.2	37.0

Adapted annotation scheme, better for automatic processing

Conclusion

Best methods:

	Precision	Recall	F-Score
Ungrammaticality	72.8	49.1	58.6
Datelines	86.0	89.7	87.8
Redundancy	58.0	28.2	37.0

Adapted annotation scheme, better for automatic processing

Tool will be made available to annotate with our methods

Future Work

Other violations

- pronouns: coreference resolution
- acronyms: finding full form near first unexpanded form
- mentions & noun phrases: NER + ?
- no semantic relatedness: semantic parsing? Wordnet distance?
- no discourse relation: discourse parsing, does connective match relation?

Future Work

Ungrammaticality

- detection methods for other subtypes

Future Work

Ungrammaticality

- detection methods for other subtypes

Redundancy

- include contextual information
- include source document information
- semantic approaches

Future Work

Ungrammaticality

- detection methods for other subtypes

Redundancy

- include contextual information
- include source document information
- semantic approaches

Corpus

- annotate a corpus with subtypes, sentence based
- evaluate methods on other data sets/corpora/domains

References

Breiman, L. (2001). Random forests. *Machine learning*, 45(1):5–32.

Finkel, J. R., Grenager, T., and Manning, C. (2005). Incorporating non-local information into information extraction systems by gibbs sampling. In *Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics*, pages 363–370. Association for Computational Linguistics.

Friedrich, A., Valeeva, M., and Palmer, A. (2014). Lqvsumm: A corpus of linguistic quality violations in multi-document summarization.

Manning, C. D., Surdeanu, M., Bauer, J., Finkel, J., Bethard, S. J., and McClosky, D. (2014). The Stanford CoreNLP natural language processing toolkit. In *Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 55–60.

Owczarzak, K. and Dang, H. T. (2011). Overview of the tac 2011 summarization track: Guided task and aesop task. In *Proceedings of the Text Analysis Conference (TAC 2011), Gaithersburg, Maryland, USA, November*.

Packart, W. (2011). ACE: the Answer Constraint Engine. `http://sweaglesw.org/linguistics/ace/`. Accessed: 2014-08-20.

Bonus Slide: Full **UnknownTokens** Evaluation

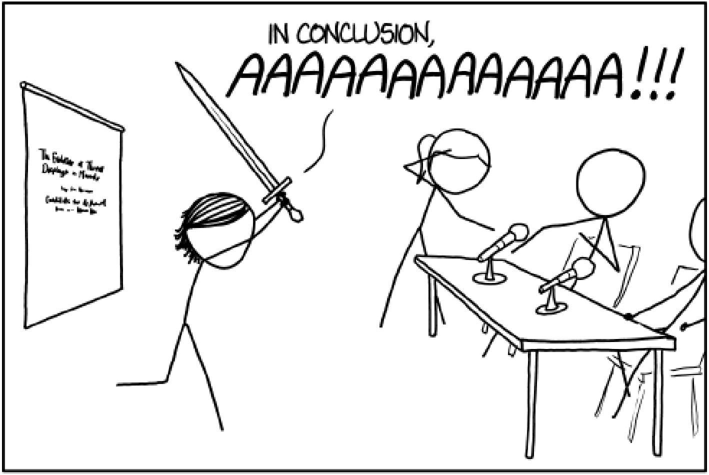
	Missing spaces			No missing spaces		
	P	**R**	**F**	**P**	**R**	**F**
Baseline	0.0	0.0	0.0	94.8	**100**	97.3
$\mathrm{UT}_{\mathrm{gw}}$	15.0	**98.7**	26.0	**99.9**	69.1	81.7
$\mathrm{UT}_{\mathrm{gw+heur}}$	30.5	97.3	46.5	99.8	87.8	93.4
$\mathrm{UT}_{\mathrm{gw+heur+ner}}$	35.5	97.3	52.0	99.8	90.3	94.8
$\mathrm{UT}_{\mathrm{gw+heur+ner+wiki}}$	70.3	96.0	81.2	99.8	97.8	98.8
$\mathrm{UT}_{\mathrm{source}}$	**95.9**	94.6	**95.2**	99.7	99.7	**99.7**

Bonus Slide: **RandomForest**: Evaluation of all classes

	Precision	**Recall**	**F-Score**
Ungrammatical	72.8	49.1	58.6

Bonus Slide: **RandomForest**: Evaluation of all classes

	Precision	**Recall**	**F-Score**
Ungrammatical	72.8	49.1	58.6
Not ungrammatical	86.6	94.7	90.5
Weighted Average	83.5	84.5	83.4



THE BEST THESIS DEFENSE IS A GOOD THESIS OFFENSE.