Intrinsic Evaluation of Summarization Datasets

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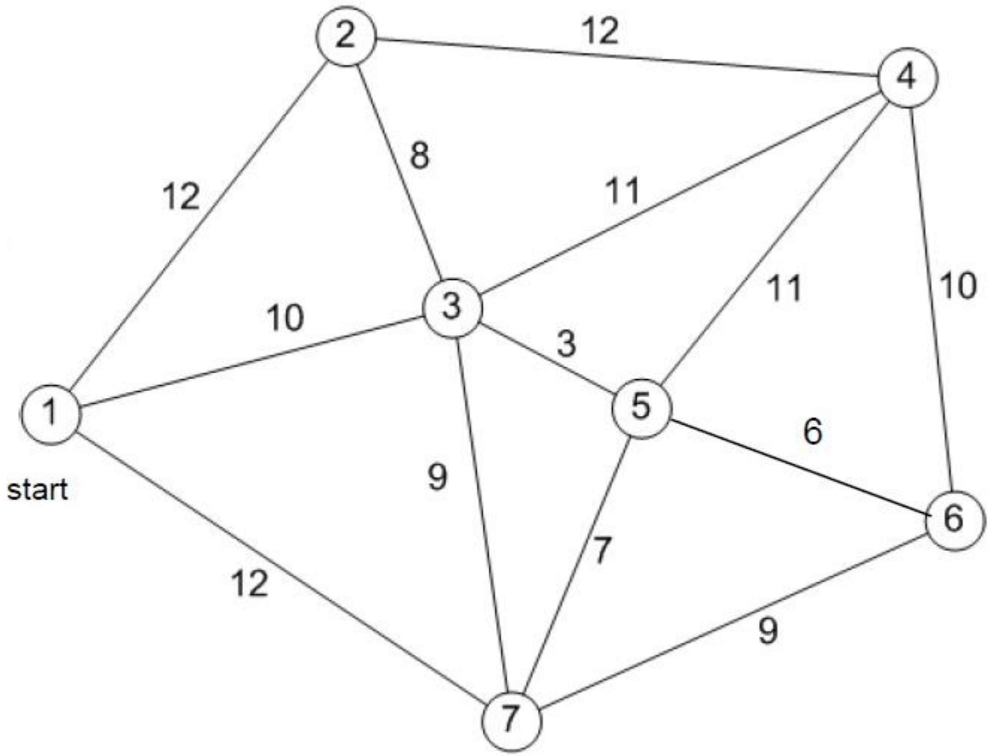
KEYNOTE!!!

Revisit
Summarization Data

Ensuring data quality

- Crowdsourcing practices
  - NLVR, NLVR2 from Yoav Artzi's group at Cornell
  - Several commonsense datasets from Yejin Choi's group at UW/AI2
  - Adversarial filtering, human-in-the-loop generation
- WMT
- Penn Treebank

Is evaluating data quality easy?



Travelling Salesman Problem

Find shortest cycle that starts and ends at 1, such that you reach every vertex.

NP-Hard

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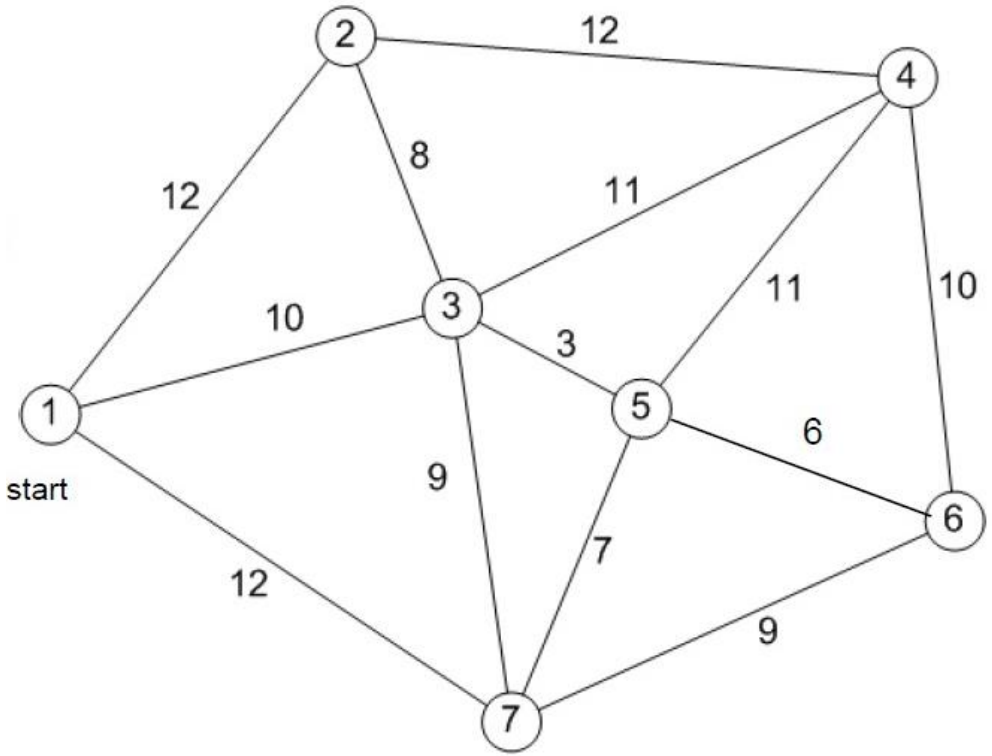
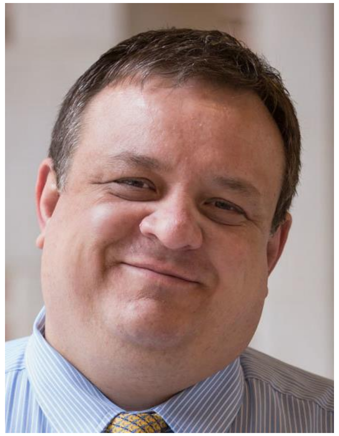


Trav. Sale. Decision Problem

Does there exist a solution to TSP of cost at most L?

NP-Hard






What do we do?

- Identify important aspects of summarization data

- Measure each of these aspects

Properties we measure

1. Compression **(CMP)**
2. Abstractivity **(ABS)**
3. Topic Similarity **(TS)**
4. Redundancy **(RED)**
5. Semantic Coherence **(SC)**

A taste of the measures: Topic Similarity

$$\mathbf{TS}\left(D_i, S_i\right) = 1 - \mathrm{JS}(\theta_{D_i|\mathcal{M}}, \theta_{S_i|\mathcal{M}})$$

M – LDA topic model learned on reference documents in dataset

JS – Jensen-Shannon distance

θ – Inferred topic distributions under *M*

A taste of the measures: Semantic Coherence

$$\mathbf{SC}\left(S_i\right) = \frac{\sum_{j=2}^{||S||} \mathbb{1}_{\mathrm{BERT}\left(S_i^j \mid S_i^{j-1}\right)}}{||S_i|| - 1}$$

S_i^j – Sentence *j* in summary *i*

$\boldsymbol{BERT}\left(S_i^j | S_i^{j-1}\right)$ – Next-sentence prediction under $\boldsymbol{BERT}$ of S_i^j given S_i^{j-1}

$||S_i||$ – Length of summary S_i in sentences

Compression captures dataset type

	News					Scientific		Social Media	Meeting	Script
	CNN-DM	**NYT**	**NWS**	**GW**	**XSum**	**PeerRead**	**PubMed**	**TL;DR**	**AMI**	**MovieScript**
# ex.	287K	655K	995K	3804K	203K	9963	21K	3084K	97	1061
avg. $\lvert D_i \rvert$	717	822	677	34	438	1203	2394	238	6020	28K
avg. $\lvert S_i \rvert$	50	46	40	9.6	24	160	270	27	314	122
avg. $\lVert D_i \rVert$	31	34	26	1	19	54	95	11	568	3156
avg. $\lVert S_i \rVert$	3.52	1.00	1.75	1.00	1.00	6.10	10.0	1.71	17.1	5.14
CMP$_w$	0.909	0.869	0.910	0.714	0.904	0.763	0.870	0.876	0.941	0.994
CMP$_s$	0.838	0.915	0.890	0.001	0.902	0.765	0.874	0.811	0.964	0.998
TS	0.634	0.586	0.539	0.478	0.578	0.702	0.774	0.438	0.573	0.547
ABS$_1$	0.135	0.249	0.191	0.334	0.346	0.201	0.122	0.384	0.184	0.147
RED	0.157	-	0.037	-	-	0.168	0.17	0.056	0.215	0.152
SC	0.964	-	0.981	-	-	0.994	0.990	0.961	0.968	0.983

Table 1: **Upper half**: Standard dataset statistics. **Lower half**: Aspect-level scores for each dataset (0 is minimal value, 1 is maximal value). Corresponding standard deviations appear in Table 9. Redundancy and semantic coherence are not reported for datasets with $>95\%$ single-sentence summaries.

Mismatch between dataset and modelling (abstractive vs. extractive)

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Since datasets feature significant redundancy, we may need to post-process to deploy systems

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Extra Results in Paper

1. Pairwise correlations between metrics
2. Standard deviations for metrics
3. Other metrics we tried for measuring same properties

What happens for “extreme” examples

Extreme – Top or bottom 10% of examples in a given dataset for a given metric

Manually examine several hundred such examples

Noticed that extremes often correlate with being generically low quality (for a conservative notion of low quality)

Fraction of low quality examples

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CMP_w ↑	50	50	70	60	30	10	10	80	0	10
ABS_1 ↑	40	30	70	50	50	70	50	80	0	10
CMP_w ↓	20	50	40	10	40	70	20	30	0	10
ABS_1 ↓	30	10	30	0	50	10	0	50	0	10

Table 3: **Upper half**: Percent of examples sampled from the top (↑) 10% for the given metric that were low quality. **Lower half**: Percent of examples sampled from the bottom (↓) 10% for the given metric that were low quality.

Original Text (truncated): Brodie (the dog) was neglected, and ended up with serious anger and health issues concerning his skin and allergies. My boyfriend adopted him ...

Summary: Onions.

Detector: Extremely High Compression

Figure 8: **Dataset: TL;DR**. We observe this trend quite frequently in **TL;DR**. Specifically, since authors on the social discussion platform Reddit choose to provide these summaries at their discretion, we often find the "summaries" are attention-grabbing and serve a starkly different rhetorical purpose from how summaries are generally conceived.

Original Text (truncated): these are external links and will open in a new window1908 - king carlos and eldest son assassinated in lisbon. second son manuel becomes king. 1910 - king manuel ii abdicates amid revolution ...

Summary: a chronology of key events :

Detector: Extremely High Compression

Figure 9: **Dataset: XSum**. We observe this trend quite frequently in **XSum**. For articles that are essentially timelines or other types of chronologies discussing historic events diachronically (which forms a small but distinctive section of the writing style of BBC from our analysis), the summary extracted to accompany it is generally this string or a slightly altered version. We argue this summary is fairly unhelpful (and is likely fairly uninteresting to test models on; simple rule-based filtering made be preferable to avoid overestimating performance on this dataset because of these examples).

Original Text (truncated): a lógica é o estudo dos princípios e critéiros de inferências e demonstrações válidas. um sistema lógico é composto por três partes: a sintaxe (ou notação), ...

Summary (truncated): logic is the science of correct inferences and a logical system is a tool to prove assertions in a certain logic in a correct way ...

Detector: Extremely High Abstraction

Figure 3: **Dataset: PeerRead**. This summary simply is not in the same language and hence achieves a very high abstractivity.

Original Text: BASEBALL American League BALTIMORE ORIOLES – Agreed to terms with INF-OF Mark McLemore on a minor league contract. BOSTON RED SOX – Named Dale Sveum third base coach.

Summary: Sports transactions

Detector: Extremely High Abstraction

Figure 5: **Dataset: NYT**. This summary is unlikely to be informative to someone who has not read the reference document and is more of a categorization/label than a summary. This is similar to the previous **NYT** example given.

Discussion

- How do we handle low quality examples
  - Prune, provide new reference summaries, keep as is, …
- Same types of ideas applied beyond summarization
- Only English language, single doc., single ref. summary

- **Higher scrutiny for future summarization datasets**
- **More deliberate in choosing datasets in modelling**