# Reading and using CS research

A case study: summarization

### Introduction

### Hi, I'm Abe.

#### Student in NLP at UMass: http://slanglab.cs.umass.edu/

I'm in my 4nd year of the MS/PhD program

Before I became interested in NLP, I worked as a software developer and data journalist

http://www.abehandler.com



I am not an expert researcher! I'm just a grad student sharing what I have learned

### **IBM** Watson



# You can do neat stuff without fancy research methods

### So why bother with research?

- CS researcher and you want to do research
- You are a curious person and you want to understand the world around you
- You are on a team that uses research methods

## You have a problem that does not have an established solution!

databases vs. summarization

### Rookie demo

Find out about a news topic. Build an interactive summary.

Why is Rookie different?

- Interactive speed
  - Waiting a few seconds for a program is unacceptable
- Criteria for success
  - Task-based. Not supervised learning.
  - What is a "summary"?
- No method does what it needs





### Summarization

Given a collection of one or more documents of length L, produce a short passage that both reads fluidly and includes the "most crucial" information from L.

#### "summarization"

- Compress a sentence
- Generate a headline
- Compress an article
- Compress lots of articles
- Delete words
- Generate paraphrases
- Query-focused
- Structured
- Domain-specific

### What's going on today in the pioneer valley?





### General research tips

Make a notation sheet

Find a survey paper

Check conferences for recent work

- In NLP: NACCL, ACL, EMNLP, TACL

Learn the "big names" of people who publish in an area

Has this been done? How can you modify existing work?

What is different or unique about your approach?

- Corpus, method, linguistics, math, formalism, application ....

### Advice: Big names

### Learning the "big names". For summarization:

- Kathleen McKeown
- Sasha Rush
- Regina Barzilay

### How to find the "big names"?

- Read a bunch of papers
- https://www.semanticscholar.org
  - Limit to NLP conferences, turn on the author facets. The big names "pop out".

## Advice: find a survey paper

When you start a research project, you often don't even know what you are trying to do.

### **Das and Martin**

A <u>Survey</u> on Automatic Text Summarization

- Really old problem (1960s)
- Many formulations
- Lots of disagreement on what you are trying to do
  - Preserve "useful" information
  - Be shorter (compression rate parameter)

## Advice: learn the lingo, notation and key concepts

### Lingo and notation

- In this class, you try to use consistent names/terms/notation.
- In research, this is often not the case.
- Especially if you want to bridge communities.

### Summarization lingo

- Extraction
- Abstraction
- Fusion
- Single vs. multi document
- "Query-focused"
- Sentence compression
- DUC (document understanding conference)
- TREC (text retrieval conference)

### Is extractive or abstractive summarization easier?

WASHINGTON — Over the past two decades, <u>Taiwan</u> has slipped from its position atop the list of flash points in the complex relationship between the United States and <u>China</u>. In meetings between President Obama and President Xi Jinping of China, it has typically come up after half a dozen more pressing issues, like trade, cyberattacks and Beijing's aggressive moves in the South China Sea.

Now, though, in a single protocol-shattering phone call with the president of Taiwan, President-elect <u>Donald J. Trump</u> has thrust it back on the table. Not since President Richard M. Nixon met with Mao Zedong in 1972 — when the two issued the Shanghai Communiqué clarifying the status of Taiwan — has an American leader so shaken up the diplomatic status quo on the issue.

"Taiwan is about to become a more prominent feature of the overall U.S.-China relationship," said Jon M. Huntsman, who served as ambassador to China during Mr. Obama's first term. "As a businessman, Donald Trump is used to looking for leverage in any relationship. A President Trump is likely to see Taiwan as a useful leverage point."

## Step one: how to find important words?

### Some approaches

- word frequency (Luhn 1958)
- word importance (tf-idf, pmi)
- word position: super useful (e.g. scientific abstracts, news...)
- key phrases. "significant" and "we can see that"
- "statistical revolution" (1990s)
- neural networks return (last few years)

# Why not just count the most frequent words?

### Tf-idf \*

- Term frequency = how many times a word type occurs in a document
- Inverse document frequency = 1/(count of documents that contain a word)
- Tf-idf score = tf \* idf

\* many very similar formulations

### Intuition tf-idf

- You have a corpus of 10,000 recent NYT world news articles

- Of 10,000 articles total, 100 contain the word Taiwan
  - document frequency = 100
  - Inverse document frequency = 1/100 = 1/100

- Say 2000 contain the word Obama
  - document frequency = 2000
  - Inverse document frequency = 1/2000

### TF and IDF

- TF => how many times a term was mentioned
- DF => how many documents contain that term
- IDF => 1/DF

### tf-idf is only one way to find important words

- PMI
- Importance to a "topic" (LDA)
- Proximity to a query word in vector space
- Raw count
- Many more...

### Say you searched Google for "Amherst, MA"

### What words would have high term frequencies?

What words would have low document frequencies?

WASHINGTON — Over the past two decades, <u>Taiwan</u> has slipped from its position atop the list of flash points in the complex relationship between the United States and <u>China</u>. In meetings between President Obama and President Xi Jinping of China, it has typically come up after half a dozen more pressing issues, like trade, cyberattacks and Beijing's aggressive moves in the South China Sea.

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A summary that favors the word Taiwan (tf-idf = 5/100), drops Obama (tf-idf = 2/2000) In meetings between President

Obama and President Xi Jinping of China, it has typically come up after half a dozen more pressing issues, like trade, cyberattacks and Beijing's aggressive moves in the South China Sea.



"Taiwan is about to become a more prominent feature of the overall U.S.-China relationship," said Jon M. Huntsman, who served as ambassador to China during Mr. Obama's first term. A summary that favors the word Obama (2/2000) and drops Taiwan tf-idf = 5/100

### Which summary is better?

## Why?

What other kinds of information would you need besides word importance to make a summary?

### How to win DUC 2002

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• h/t Chris Kenzie (Columbia PhD student)
# Are these examples extractive or abstractive?



#### **Evaluation**:

## How do you know a summarization method is good?

When you read a paper: why do you believe the authors?

## Human evaluation: How could you test a summarization system on people?

#### What are the downsides to this method?

#### Automatic evaluation

#### ROUGE-N: how many N-grams from gold did you get?

**Input**: President Donald Trump fired another warning shot Sunday at U.S. companies considering moving their operations out of the country, threatening "retributions or consequences" such as a hefty border tax if they do.

**"Gold standard":** Donald **Trump** threatened to penalize **companies** who move jobs **out of the country**.

**Some system: Trump** fired shot at **companies** moving operations **out of the country**.

ROUGE-1 = 6/13

ROUGE-2 = 3/12

#### Who can find a problem with ROUGE-N?



#### Switch from summarization to translation in next examples

#### Gaming automatic evaluation (precision)

Precision: what percentage of the words in your translation occur in the reference translation?



### Precision = total correct / total guesses

#### Gaming automatic evaluation (precision)

Precision: what percentage of the words in your candidate (machine) translation occur in the reference translation?

**Input**: el gato esta en la estera **Output**: the the the the the the **Human**: The cat is on the mat

#### 6 out of 6!

Precision = total correct / total guesses

#### Who can defend ROUGE-N?



- clear - simple - interpretable - fast

#### Defense of ROUGE-N

English Spanish French Detect language -	÷.	English Spanish Arabic - Translate	
This is amazing.	×	Esto es increíble.	
		☆ □ ● <	这 🧪 Suggest an edit

	BLEU	Log Perplexity	Decoding time (s)
CPU	31.20	1.4553	1322
GPU	31.20	1.4553	3028
TPU	31.21	1.4626	384

https://arxiv.org/pdf/1609.08144v2.pdf

#### **BLEU** scores

We compute the brevity penalty BP,

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \le r \end{cases}.$$

-

Then,

BLEU= BP 
$$\cdot \exp\left(\sum_{n=1}^N w_n \log p_n\right)$$
.

The ranking behavior is more immediately apparent in the log domain,

log BLEU = min
$$(1 - \frac{r}{c}, 0) + \sum_{n=1}^{N} w_n \log p_n$$
.  
http://www.aclweb.org/anthology/P02-1040.pdf

### The BLEU score matches human judgement (in some way)





**Human Judgments** 

Source :http://web.stanford.edu/class/cs224n/handouts/cs224n-lecture3-MT.pdf

#### Too much BLEU?

People started optimizing their systems to maximize BLEU score – BLEU scores improved rapidly. The correlation between BLEU and human judgments of quality went way, way down

Coming up with automatic MT evaluations has become its own research field – TER, METEOR, MaxSim, SEPIA, RTE-MT, TERPA

Source :http://web.stanford.edu/class/cs224n/handouts/cs224n-lecture3-MT.pdf

#### Takeaways

- Without evaluation, you are arguably not doing science
- Auto evaluation is helpful
- Clear, simple, interpretable evaluations are also good
- Human judgement is the ultimate evaluation. If your translation is very choppy or makes no sense, but has a great BLEU score, nobody cares.
- Research communities have set ways of evaluating things. If you submitted a paper on a summarization technique with no ROGUE score, people would not trust your technique.

### Oh yeah, machine learning ...

#### Machine learning approaches (via Das)

naive Bayes: Edmunson 1969 and Kupiec 1995

- features (e.g. position, cue words, tf-idf scores)
- classes (class 1 = included, class 2 = not included)

- **HMMs**: Conroy and O'Leary. Sequence model where each sentence gets 1,0 inclusion

- CRFs: Lu Wang. A Sentence Compression Based Framework to Query-Focused Multi-Document Summarization

#### Where do "gold" summaries come from?

#### Where does this training data come from?

'Don't believe a thing you hear, unless it comes from me': Megyn Kelly responds to reports she is leaving Fox News for CNN by urging fans to ignore rumors - but doesn't rule the move out

- Megyn Kelly says there is no truth that CNN is reportedly trying to get her to join the network when her Fox News contract expires in July
- But she did not rule out the move, and told fans to only believe information that comes from her
- Last week, an insider told Drudge Report the network wanted Kelly to anchor either the 8pm or 9pm hour on weeknights
- Reports suggested CNN would not match the \$20million offer Fox News has already put on the table to get Kelly to re-sign her contract

http://www.dailymail.co.uk/news/article-3998964/Megyn-Kelly-responds-rumors-leaving-Fox-CNN-saying-don-t-believe-thing.html





## OMG papers



#### arXiv.org

Open access to 1,456,318 e-prints in Physics, Mathematics, Computer Science, Quantitative Biology, Quantitative Finance, Statistics, Electrical Engineering and Systems Science, and Economics Subject search and browse: Physics Search Form Interface Catchup

5 Sept 2018 arXiv looks to the future with move to Cornell CIS

23 Jul 2018: Theoretical Economics and General Economics subject areas added to arXiv

18 Jul 2018: Search interface updated to version 0.4

See cumulative "What's New" pages. Read robots beware before attempting any automated download

#### **Physics**

 Astrophysics (astro-ph new, recent, search) includes: Astrophysics of Galaxies: Cosmology a

includes: Astrophysics of Galaxies; Cosmology and Nongalactic Astrophysics; Earth and Planetary Astrophysics; High Energy Astrophysical Phenomena; Instrumentation and Methods for Astrophysics; Solar and Stellar Astrophysics • Condensed Matter (cond-mat new, recent, search)

- includes: Disordered Systems and Neural Networks; Materials Science; Mesoscale and Nanoscale Physics; Other Condensed Matter; Quantum Gases; Soft Condensed Matter; Statistical Mechanics; Strongly Correlated Electrons; Superconductivity
- General Relativity and Quantum Cosmology (gr-qc new, recent, search)
- High Energy Physics Experiment (hep-ex new, recent, search)
- High Energy Physics Lattice (hep-lat new, recent, search)
- High Energy Physics Phenomenology (hep-ph new, recent, search)
- High Energy Physics Theory (hep-th new, recent, search)
- Mathematical Physics (math-ph new, recent, search)
- Nonlinear Sciences (nlin new, recent, search) includes: Adaptation and Self-Organizing Systems: Cellul
- includes: Adaptation and Self-Organizing Systems; Cellular Automata and Lattice Gases; Chaotic Dynamics; Exactly Solvable and Integrable Systems; Pattern Formation and Solitons
- Nuclear Experiment (nucl-ex new, recent, search)
- Nuclear Theory (nucl-th new, recent, search)
- · Physics (physics new, recent, search)

includes: Accelerator Physics; Applied Physics; Atmospheric and Oceanic Physics; Atomic Physics; Atomic and Molecular Clusters; Biological Physics; Chemical Physics; Classical Physics; Computational Physics; Data Analysis, Statistics and Probability; Fluid Dynamics; General Physics; Ceophysics; History and Philosophy of Physics; Instrumentation and Detectors; Medical Physics; Optics; Physics Education; Physics and Society; Plasma Physics; Popular Physics; Space Physics

Quantum Physics (quant-ph new, recent, search)



#### semanticscholar.org

Semantic Scho	blar	summarization	SIGN IN
Filter Results:		Page 1	Sort by: Relevance \$
Field of Study	~	Video Summarization using Deep Semantic Features	Trending
Publication Year	^	<u>Mayu Otani, Yuta Nakashima, Esa Rahtu, Janne Heikkilä, Naokazu Yokoya</u> • ArXiv • 2016 This paper presents a video <b>summarization</b> technique for an Internet video to provide a quick way to	o overview its content. This is a
1975	2017	challenging problem because finding important or informative parts of the original video requires to ur the content of Internet videos is very diverse, ranging from home videos to documentaries, (More) Mentioned in 1 tweet:	nderstand its content. Furthermore
Publication Type	~	arxiv @arxiv_org	
Author	$\sim$	Video Summarization using Deep Semantic Features.	
Key Phrase	~	3:34 AM - 30 Sep 2016	
Publication Venue	~	<h 1<="" 2="" th="" t⊋="" ♥=""><th></th></h>	
Data Set Used	~	View On ArXiv V Related Publications More	
Brain Region	~		
Cell Type	~	Mining and summarizing customer reviews	



- The author is someone who you know to do good work
  - Michael Collins, Regina Barzilay, Tommi Jaakkola, Percy Liang, Chris Manning
- The author is in a lab with people you know to do good work
- The paper is very well-written
- The paper has pretty graphics that demonstrate care and attention to detail
- The paper is cited favorably by a source you trust
- The paper won an award at a good conference
- The paper cites work you know is relevant in the field
- The paper is cited a lot
- The paper is on a syllabus from someone you trust
  - http://www.cc.gatech.edu/~jeisenst/

# Those heuristics can be totally wrong

### Science is a social process

# Fast forward to the "state-of-the-art"

(or at least something getting lots of recent attention)

#### Rush, Chopra, Weston (2015)

A Neural Attention Model for Sentence Summarization

#### Why is this the state of the art?

Decoder	Model	Cons.	<b>R-1</b>	R-2	R-L
Greedy	ABS+	Abs	26.67	6.72	21.70
Beam	BoW	Abs	22.15	4.60	18.23
Beam	ABS+	Ext	27.89	7.56	22.84
Beam	ABS+	Abs	28.48	8.91	23.97

Table 3: ROUGE scores on DUC-2003 development data for various versions of inference. Greedy and Beam are described in Section 4. Ext. is a purely extractive version of the system (Eq. 2)

# What is this paper trying to do?

#### Example One: Person or machine?

**Input:** a detained iranian-american academic accused of acting against national security has been released from a tehran prison after a hefty bail was posted , a top judiciary official said tuesday

Person or machine? iranian-american academic held in tehran released on bail

**Person or machine?** detained iranian-american academic released from jail after posting bail

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Real headline: iranian-american academic held in tehran released on bail

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- Synonyms, morphology
# Example (2)

**Input:** the white house on thursday warned iran of possible new sanctions after the un nuclear watchdog reported that tehran had begun sensitive nuclear work at a key site in defiance of un resolutions

Real headline: us warns iran of step backward on nuclear issue

Model: iran warns of possible new sanctions on nuclear work

- Something is deeply wrong with the model's output here.
- Can ROUGE-1 detect it? Can ROUGE-2?

# What data do they use?

"The standard sentence summarization evaluation set is associated with the DUC-2003 and DUC-2004 shared tasks"

Science is a social process.

# Input and output

Input: **x** 

Output: y

Where **|x|** >> **|y|** 

Considers a context of c words

# A generative model





## Training loss function

$$\begin{split} \mathrm{NLL}(\theta) &= -\sum_{j=1}^{J} \log p(\mathbf{y}^{(j)} | \mathbf{x}^{(j)}; \theta), \\ &= -\sum_{j=1}^{J} \sum_{i=1}^{N-1} \log p(\mathbf{y}^{(j)}_{i+1} | \mathbf{x}^{(j)}, \mathbf{y}_{\mathrm{c}}; \theta). \end{split}$$

J = summary pairs



### Beam search decoding

Output 1 Output 2 Output 3 Output 4 US US US US China China China China spoke spoke spoke spoke ran ran ran ran tariff tariff tariff tariff

#### Beam search



# Practical note: summarization for hackers

- Put sentences in a search engine and query
- Select sentences with query words
- KWIC viewers

#### $\Theta \Theta \Theta$

term	local		global	lift	
Term Prob >=	5 out of 10	,000	¢Co	ount >= 1	1(
Docvar-assoc	iated terms	356/	8842 ter	ms	
Docvar-associ	iated terms	356/ gl	8842 ter obal	ins	
Docvar-associ term hella	iated terms	356/	8842 ter obal 90	rms	
Docvar-associ term hella la broke	local 18 15	356/ gl	8842 ter obal 90 196 189	ms lift 2.979 2.265	
Docvar-associ term <mark>hella</mark> la broke which	iated terms	356/ gl	8842 ter obal 90 196 189 260	ms lift 2.979 2.265 2.096	
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term	local	global		lift	11 I.I.	
hella	90	;	90	9.898	0	
idk	44	- 2	314	1.387		
nigga	48	1	368	1.291		
tho	42	:	325	1.279		
wtf	46		361	1.261		
mad	47	1	378	1.231		
b	42	:	340	1.223		
smh	46	:	380	1.198		
lil	45	:	382	1.166		
hit	56	00	478	1.160		
face	44		382	1 1 4 0		



icking veins and arteries .. looks hella hard no joke . i hope i do better user18921

breeendaong he's like 90 pound hella big !! @teampranksta wen u gu user19604

to the movies n bought me food **hella** times ! definitley a fair trade . u user23555

a columbine hilltop @daiyonnie hella late follow me on instagram i on user23724

i haven't gone to sleep drunk in **hella** long i just watched a suv glide a nel no i didn't win anything . i'm **hella** down right now . @cherilynna v What did they measure?

Does the measurement support their argument?

# **Rookie evaluation**



"As journalists, it's important to have a large-view grasp of a story before writing about it. □ This system could be helpful in providing both a snapshot and an ability to then dive deeper into your story"

candidate set generation task							
	¥						
Jean-Bertrand Aristide restored to power under watch of United States	Jean-Bertrand Aristide restored to power under watch of United States						
claimed the United States said that Rev. Jean-Bertrand Aristide wanted to	United States ousted former President Jean-Bertrand Aristide						
by the United States since the Rev. Jean-Bertrand Aristide argued	Candidate set						
Jean-Bertrand Aristide, left Haiti for the United States in March		construction					
the United States ousted former President Jean-Bertrand Aristide to	<b>Jean-Bertrand Aristide</b> restored to power under watch of United States United States ousted former President Jean-Bertrand Aristide	task					
Mention set	Summary						

Sentence. Pakistan launched a search for its missing ambassador to Afghanistan on Tues-

day, a day after he disappeared in a Taliban area.

Headline. Pakistan searches for missing ambassador.

"Gold" compression. Pakistan launched a search for its missing ambassador.

Alternate 1. Pakistan launched a search for its missing ambassador to Afghanistan on

Tuesday. (A(c) = -1.367, BREVITY = 84 characters max., IMPORTANCE = 1)

Alternate 2. Pakistan launched search Tuesday. (A(c) = -6.144, BREVITY = 59 characters

max., IMPORTANCE = 0)



# True or False?

Bertrand Aristide fled Haiti?

Bertrand Aristide was a priest?

Bertrand Aristide was President of Haiti?