
Corpus Acquisition from the Internet

Philipp Koehn

partially based on slides from Christian Buck

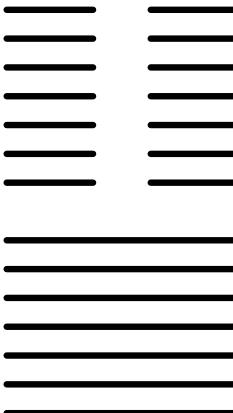
8 November 2022





Big Data

For many language pairs, lots of text available.

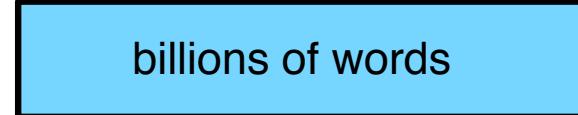


**Text you read
in your lifetime**



300 million words

**Translated text
available**



billions of words

**English text
available**



trillions of words

Mining the Web

- Largest source for text: the World Wide Web

Common Crawl



- publicly available crawl of the web
- hosted by Amazon Web Services, but can be downloaded
- regularly updated (semi-annual)
- 2-4 billion web pages per crawl
- Currently filling up hard drives in our lab

Monolingual Data

- Starting point: 35TB of text

Monolingual Data

- Starting point: 35TB of text
- Processing pipeline [Buck et al., 2014]
 - language detection
 - deduplication
 - normalization of Unicode characters
 - sentence splitting

Monolingual Data

- Starting point: 35TB of text
- Processing pipeline [Buck et al., 2014]
 - language detection
 - deduplication
 - normalization of Unicode characters
 - sentence splitting
- Obtained corpora

Language	Lines (B)	Tokens (B)	Bytes	BLEU (WMT)
English	59.13	975.63	5.14 TB	-
German	3.87	51.93	317.46 GB	+0.5
Spanish	3.50	62.21	337.16 GB	-
French	3.04	49.31	273.96 GB	+0.6
Russian	1.79	21.41	220.62 GB	+1.2
Czech	0.47	5.79	34.67 GB	+0.6



Parallel Data

- Basic processing pipeline [Smith et al., 2013]
 - find parallel web pages (based on URL only)
 - align document by HTML structure
 - sentence splitting and tokenization
 - sentence alignment
 - filtering (remove boilerplate)

Parallel Data

- Basic processing pipeline [Smith et al., 2013]
 - find parallel web pages (based on URL only)
 - align document by HTML structure
 - sentence splitting and tokenization
 - sentence alignment
 - filtering (remove boilerplate)
- Obtained corpora

	French	German	Spanish	Russian	Japanese	Chinese
Segments	10.2M	7.50M	5.67M	3.58M	1.70M	1.42M
Foreign Tokens	128M	79.9M	71.5M	34.7M	9.91M	8.14M
English Tokens	118M	87.5M	67.6M	36.7M	19.1M	14.8M
	Bengali	Farsi	Telugu	Somali	Kannada	Pashto
Segments	59.9K	44.2K	50.6K	52.6K	34.5K	28.0K
Foreign Tokens	573K	477K	336K	318K	305K	208K
English Tokens	537K	459K	358K	325K	297K	218K

- Much more work needed!

Data Cleaning and Subsampling

- Not all data useful – some may be harmful
- Removing data based on
 - domain relevance
 - alignment quality
 - redundancy
 - bad language (orthography, non-words)
 - machine translated or poorly translated
- Removing bad data always reduces training time
- Removing bad data sometimes helps quality
- Clean data approach (only using high quality data) helps in limited domains

corpus crawling

Finding Monolingual Text

- Simple Idea
 1. Download many websites
 2. Extract text from HTML
 3. Guess language of text
 4. Add to corpus
 5. Profit
- Turns out all these steps are quite involved

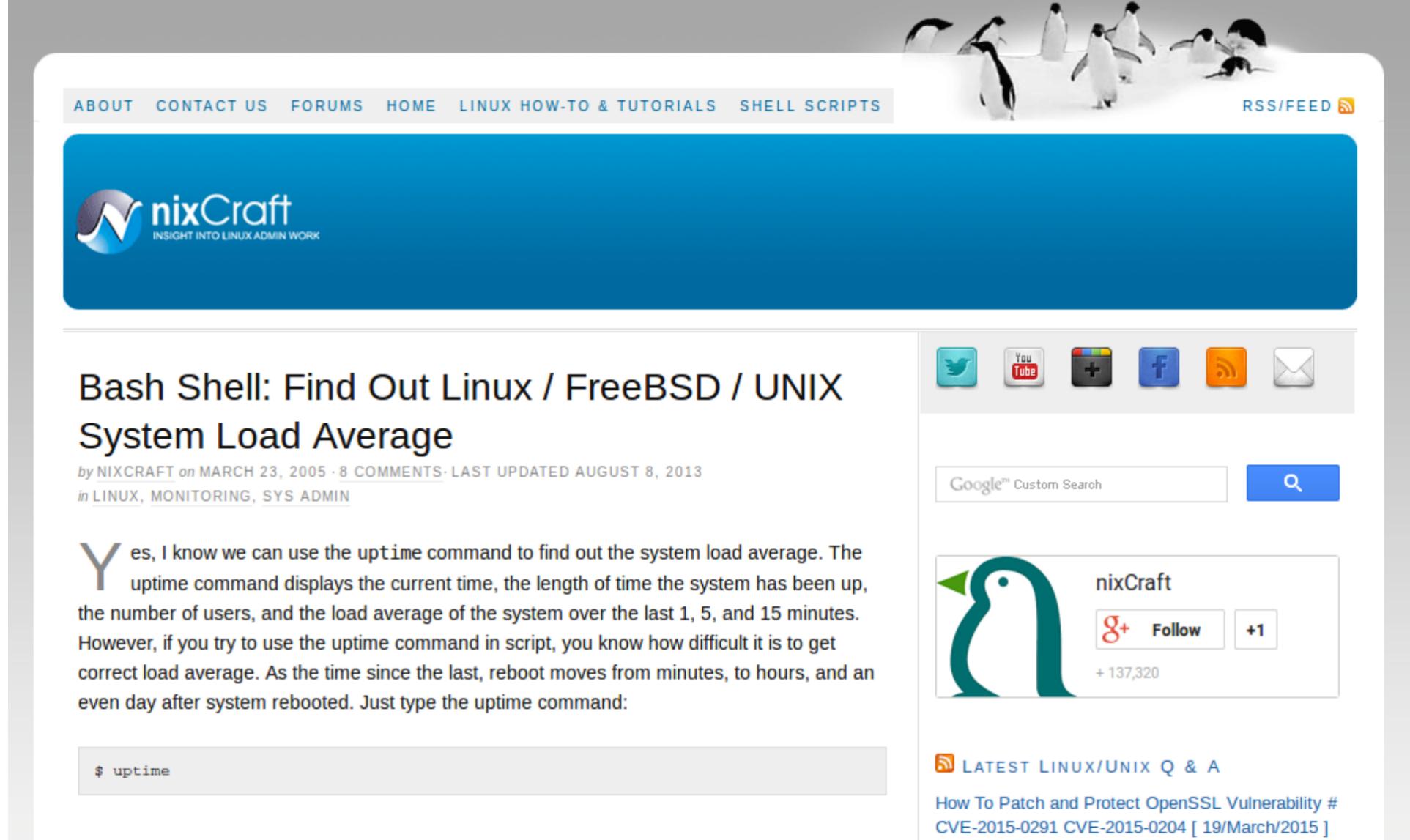


Common Crawl

- Non-profit organization
- Data
 - publicly available on Amazon S3
 - e.g. January 2015: 140TB / 1.8B pages
- Crawler
 - Apache Nutch
 - collecting pre-defined list of URLs

extracting text

A Web Page



The screenshot shows a web page from nixCraft. At the top, there's a navigation bar with links for About, Contact Us, Forums, Home, Linux How-to & Tutorials, and Shell Scripts. To the right of the navigation is an RSS/Feed icon. Below the navigation is a large blue header area featuring the nixCraft logo and the text "INSIGHT INTO LINUX ADMIN WORK". The main content area has a white background. A decorative banner at the top of the content area shows several penguins walking on ice. The main article title is "Bash Shell: Find Out Linux / FreeBSD / UNIX System Load Average", written by NIXCRAFT on March 23, 2005, with 8 comments and last updated on August 8, 2013. It includes categories for Linux, Monitoring, and Sys Admin. The article text discusses using the uptime command to find system load average. A code block shows the command "\$ uptime". On the right side of the page, there's a sidebar with social sharing icons for Twitter, YouTube, Google+, Facebook, RSS, and Email. Below that is a Google Custom Search bar. Further down is a box for the nixCraft Google+ page, which has 137,320 followers. At the bottom of the sidebar, there's a link to "LATEST LINUX/UNIX Q & A" and a news item about OpenSSL vulnerabilities.

ABOUT CONTACT US FORUMS HOME LINUX HOW-TO & TUTORIALS SHELL SCRIPTS RSS/FEED

nixCraft
INSIGHT INTO LINUX ADMIN WORK

Bash Shell: Find Out Linux / FreeBSD / UNIX System Load Average

by NIXCRAFT on MARCH 23, 2005 · 8 COMMENTS · LAST UPDATED AUGUST 8, 2013
in LINUX, MONITORING, SYS ADMIN

Yes, I know we can use the uptime command to find out the system load average. The uptime command displays the current time, the length of time the system has been up, the number of users, and the load average of the system over the last 1, 5, and 15 minutes. However, if you try to use the uptime command in script, you know how difficult it is to get correct load average. As the time since the last reboot moves from minutes, to hours, and an even day after system rebooted. Just type the uptime command:

```
$ uptime
```

 nixCraft
Follow +1
+ 137,320

LATEST LINUX/UNIX Q & A
How To Patch and Protect OpenSSL Vulnerability # CVE-2015-0291 CVE-2015-0204 [19/March/2015]



HTML Source

```
500-average.html#comments rel="nofollow">>0 comments</a></span>LAST UPDATED  
<span>LAST UPDATED  
<abbr  
51 class="updated" title="2013-08-08">August 8, 2013</abbr><span><p  
52 class='headline_meta'> in <span><a  
53 rel='tag' href='http://www.cyberciti.biz/tips/category/linux'>Linux</a>, <a  
54 rel='tag' href='http://www.cyberciti.biz/tips/category/monitoring'>Monitoring</a>, <a  
55 rel='tag' href='http://www.cyberciti.biz/tips/category/sys-admin'>Sys admin</a></span>  
</p></div><div  
56 class="format_text entry-content"><p><span  
57 class="drop_cap">Y</span>es, I know we can use the <kbd>uptime</kbd> command to find out the  
system load average. The uptime command displays the current time, the length of time the  
system has been up, the number of users, and the load average of the system over the last 1,  
5, and 15 minutes. However, if you try to use the uptime command in script, you know how  
difficult it is to get correct load average. As the time since the last, reboot moves from  
minutes, to hours, and an even day after system rebooted. Just type the uptime command:<br  
58 /> <span  
59 id="more-631"></span><br  
60 /> <code>$ uptime</code><br  
61 /> Sample outputs:</p><pre>1:09:01 up 29 min, 1 user, load average: 0.00, 0.00, 0.00</pre>  
<p>OR<br  
62 /> <code>$ uptime</code><br  
63 /> Sample outputs:</p><pre>2:13AM up 34 days, 16:15, 36 users, load averages: 1.56, 1.89,  
2.06</pre><p>Traditionally, UNIX administrators used sed and other shell command in scripting  
to get correct value of load average. Here is my own modified hack to save the time<br  
64 /> <code>$ uptime | awk -F'load averages:' '{ print $2 }'</code><br  
65 /> OR better use the following code:<br  
66 /> <code>$ uptime | awk -F'[a-z]:' '{ print $2}'</code><br  
67 /> Output taken from my <strong>OS X desktop</strong>:</p><pre> 1.24 1.34 1.35</pre><p>Output  
taken from my <strong>Ubuntu</strong> Linux server:</p><pre> 0.00, 0.01, 0.05</pre><p>Output  
taken from my <strong>RHEL</strong> based server:</p><pre> 0.24, 0.27, 0.21</pre><p>Output  
taken from my <strong>FreeBSD</strong> based server:</p><pre> 0.71, 0.71, 0.58</pre><p>Please  
note that command works on all variant of UNIX operating systems.</p><h2>See also</h2>  
<ul><li>See <a  
68 href="http://bash.cyberciti.biz/monitoring/chksysload.bash.php">chksysload.bash</a> script to
```



Method 1: Strip Tags

LAST UPDATED August 8, 2013 in Linux , Monitoring , Sys admin Yes, I know we can use the uptime command to find out the system load average. The uptime command displays the current time, the length of time the system has been up, the number of users, and the load average of the system over the last 1, 5, and 15 minutes. However, if you try to use the uptime command in script, you know how difficult it is to get correct load average. As the time since the last, reboot moves from minutes, to hours, and an even day after system rebooted. Just type the uptime command: \$ uptime Sample outputs: 1:09:01 up 29 min, 1 user, load average: 0.00, 0.00, 0.00



Method 2: HTML Parser

LAST UPDATED August 8, 2013
in Linux, Monitoring, Sys admin

Y

es, I know we can use the `uptime` command to find out the system load average. The `uptime` command displays the current time, the length of time the system has been up, the number of users, and the load average of the system over the last 1, 5, and 15 minutes. However, if you try to use the `uptime` command in script, you know how difficult it is to get correct load average. As the time since the last reboot moves from minutes, to hours, and an even day after system rebooted. Just type the `uptime` command:

```
$ uptime
```

Sample outputs: 1:09:01 up 29 min, 1 user, load average: 0.00, 0.00, 0.00

language detection

What Language?

Muitas intervenções alertaram para o facto de a política dos sucessivos governos PS, PSD e CDS, com cortes no financiamento das instituições do Ensino Superior e com a progressiva desresponsabilização do Estado das suas funções, ter conduzido a uma realidade de destruição da qualidade do Ensino Superior público.



Clues: Letter N-Grams

Muitas intervenções alertaram para o facto de a política dos sucessivos governos PS, PSD e CDS, com cortes no financiamento das instituições do Ensino Superior e com a progressiva desresponsabilização do Estado das suas funções, ter conduzido a uma realidade de destruição da qualidade do Ensino Superior público.



Example: langid.py

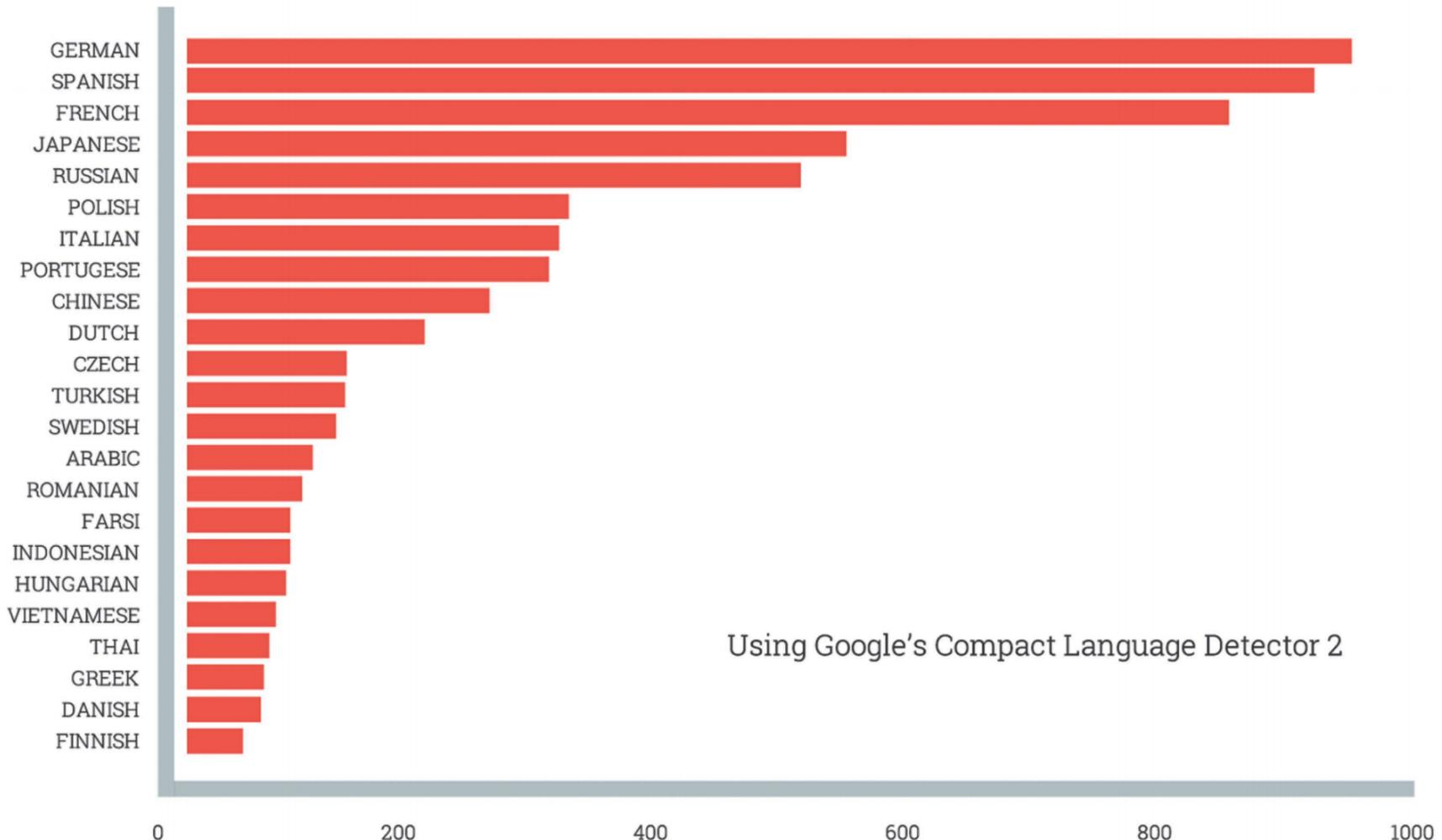
- Muitas intervenções alertaram
 - prediction: Portuguese
 - high confidence (-90.8)
- Muitas intervenções
 - prediction: Portuguese
 - fairly high confidence (-68.2)
- Muitas
 - prediction: English
 - low confidence (9.1)



Language Identification Tools

- langid.py (Lui & Baldwin, ACL 2012)
 - 1-4 grams, NaiveBayes, Feature Selection
- TextCat (based on Cavnar & Trenkle, 1994)
 - similar to langid.py
 - no Feature Selection
- Compact/Chromium Language Detector 2 (Google)
 - takes hints from tld, meta data
 - super fast
 - detects spans of text

Detected Languages in CommonCrawl



(Buck and Heafield, LREC2014)



Most Common English Phrases

Count (M)	Line
1374.44	Add to
816.33	Share
711.68	Unblock User
68.31	Sign in or sign up now!
61.26	Log in
54.77	Privacy Policy
45.18	April 2010
34.35	Load more suggestions
19.84	Buy It Now Add to watch list
16.64	Powered by WordPress.com



Benefit of Huge Language Models

	BLEU			
	2012	Δ	2013	Δ
Baseline	35.8		30.9	
+ 50M lines	36.3	0.5	31.5	0.6
+ 100M lines	36.5	0.7	31.5	0.6
+ 200M lines	36.6	0.8	31.8	0.9
+ 400M lines	37.0	1.2	31.8	0.9
+ 800M lines	37.3	1.6	31.8	0.9
+ 1.3B lines	37.7	1.9	32.0	1.1



bilingual corpus crawling

Mining Bilingual Text

- Bilingual text = same text in different languages
- Usually: one side translation of the other
- Full page or interface/content only
- Potentially translation on same page
 - e.g., Twitter, Facebook posts



Pipeline

1. Identify web sites worth crawling
2. Crawl web site
3. Language detection — as before
4. Extract text from HTML — as before
5. Align documents
6. Align sentences
7. Clean corpus



identify web sites

Targeted Crawling

- A few web sites with a lot of parallel text, e.g.,
 - European Union, e.g., proceedings of the European Parliament
 - Canadian Hansards
 - United Nations
 - Project Syndicate
 - TED Talks
 - Movie / TV show subtitles
 - Global Voices
- Hand-written tools
 - crawling
 - text extraction
 - document alignment
- Few days effort per site



OPUS is a growing collection of translated texts from the web. In the OPUS project we try to convert and align free or to provide the community with a publicly available parallel corpus. OPUS is based on open source products and the cc package. We used several tools to compile the current collection. All pre-processing is done automatically. No manual

The OPUS collection is growing! Check this page from time to time to see new data arriving ...
Contributions are very welcome! Please contact <jorg.tiedemann@lingfil.uu.se>

Search & download resources:

Search & Browse

- OPUS multilingual search interface
- Europarl v7 search interface
- Europarl v3 search interface
- OpenSubtitles search interface
- EUconst search interface
- Word Alignment Database

Tools & Info

- OPUS Wiki
- Tools for tagging and parsing
- Downloads (tools and models)

Sub-corpora (downloa

- Books - A collect
- DGT - A collecti
- DOGC - Docume
- ECB - European t
- EMEA - Europea
- The EU booksho
- EUconst - The Et
- EUOPARL v7 -
- EUOPARL - Et
- GNOME - GNOM
- The Croatian - Er
- JRC-Acquis- legi



Broad Crawling

- Identify many web sites to crawl
 - has the phrase **This page in English** or variants
 - has link to language flag
 - known to have content in multiple languages (from CommonCrawl)



Broad Crawling

- Identify many web sites to crawl
 - has the phrase **This page in English** or variants
 - has link to language flag
 - known to have content in multiple languages (from CommonCrawl)
- Follow links
 - up to n links deep into site
 - up to n links in total
 - only follow links to web pages, not images, etc.

Broad Crawling

- Identify many web sites to crawl
 - has the phrase **This page in English** or variants
 - has link to language flag
 - known to have content in multiple languages (from CommonCrawl)
- Follow links
 - up to n links deep into site
 - up to n links in total
 - only follow links to web pages, not images, etc.
- Avoid crawling sites too deeply that do not have parallel text?
(requires quick feedback from downstream processing)



document alignment

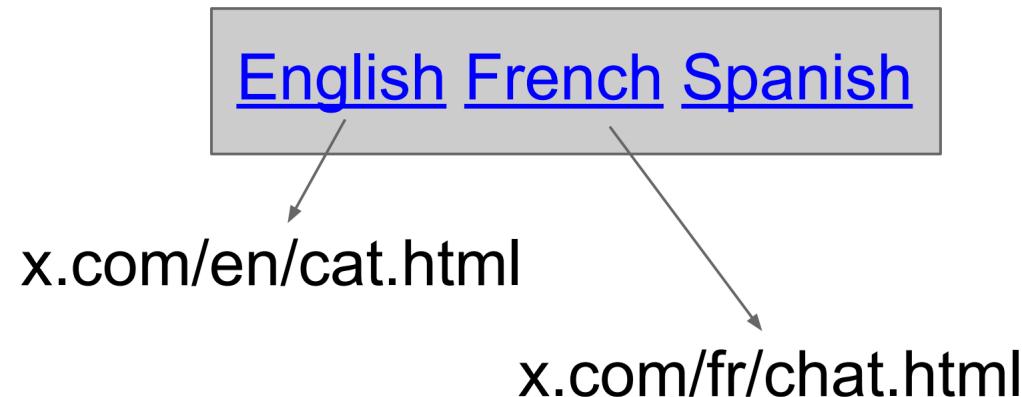
Document Alignment

- Early Work: STRAND (Resnik 1998, 1999)
(Structural Translation Recognition, Acquiring Natural Data)
- Pipeline
 1. candidate generation
 2. candidate ranking
 3. filtering
 4. optional: sentence alignment
 5. evaluation



Link Structure

- Parent page: a page that links to different language versions





Parent Page Example

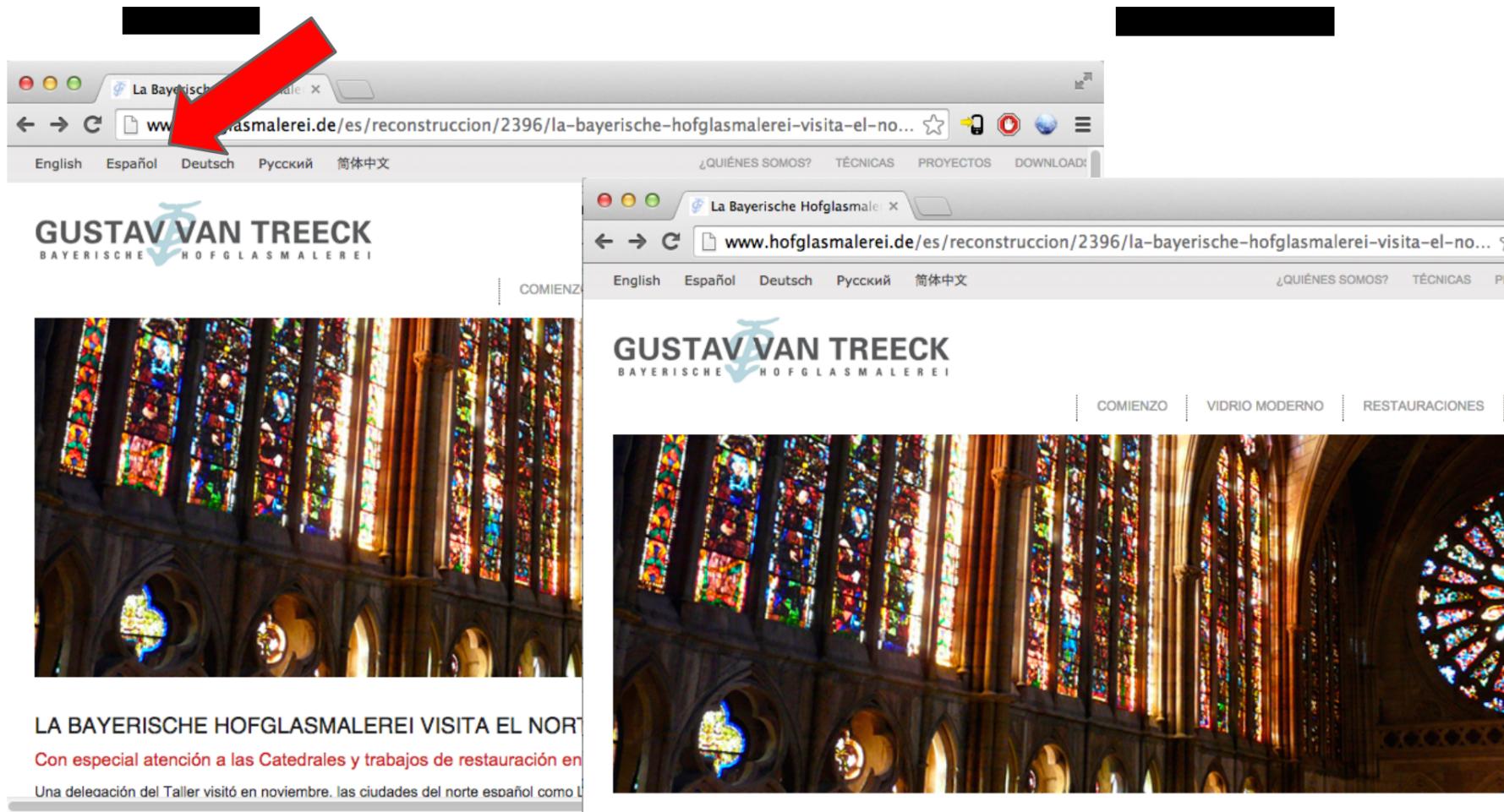
The screenshot shows a web browser window titled "Apple - Support". The address bar displays "Apple Inc. [US] https://support.apple.com/HT201361/localeselec...". Below the address bar, there are several country flags and their names arranged in a grid:

Albania	Cyprus	Česká republika
Iceland	Ireland	Macedonia
Magyarország	Malta	Moldova
Montenegro	Polska	Portugal

At the bottom of the page, a link is visible: <https://support.apple.com/pl-pl/HT201361>.

Sibling Page

- A page that links to its translation in another language



URL Matching

- Often URLs differ only slightly, often indicating language

xyz.com/en/	xyz.com/fr/
xyz.com/bla.htm	xyz.com/bla.htm?lang=FR
xyz.com/the_cat	xyz.fr/le_chat



Finding URL Patterns

- URLs with pattern =en

Count	Pattern
545875	lang=en
140420	lng=en
126434	LANG=en
110639	hl=en
99065	language=en
81471	tlng=en
56968	l=en
47504	locale=en
33656	langue=en
33503	lang=eng
19421	uil=English
15170	ln=en
14242	Language=EN
13948	lang=EN
12108	language=english
11997	lang=engcro
11646	store=en

Finding URL Patterns

- URLs with pattern lang.*=.*

Count	Pattern
13948	lang=EN
13456	language=ca
13098	switchlang=1
12960	language=zh
12890	lang=Spanish
12471	lang=th
12266	langBox=US
12108	language=english
12003	lang=cz
11997	lang=engcro
11635	lang=sl
11578	lang=d
11474	lang=lv
11376	lang=NL
11349	lang=croeng
11244	lang=English



Document Length

- Extract texts and compare lengths (Smith 2001)

$$\text{Length}(E) \approx C * \text{Length}(F)$$



learned,
language-specific parameter

- Document or sentence level

Document Object Model

37



- Translated web pages often retain similar structure

```
<html>
```

```
  <body>
```

```
    <h1>
```

Where is the cat?

```
    </h1>
```

The cat sat on
 the mat.

```
  </body>
```

```
</html>
```

```
<html>
```

```
  <body>
```

El gato se sentó
 en la alfombra.

```
  </body>
```

```
</html>
```

- This includes links to the same images, etc.



Linearized Structure

[Start:html]	[Start:html]
[Start:body]	[Start:body]
[Start:h1]	[Chunk:32bytes]
[Chunk:17bytes]	[End:body]
[End:h1]	[End:html]
[Chunk:23bytes]	
[End:body]	
[End:html]	



Levenshtein Alignment

[Start:html]	Keep
[Start:body]	Keep
[Start:h1]	Delete
[Chunk:17bytes]	Delete
[End:h1]	Delete
[Chunk:23bytes]	23 Bytes -> 32 Bytes
[End:body]	Keep
[End:html]	Keep



Content Similarity

- Simple things
 - same numbers or names in documents
 - often quite effective



Content Similarity

- Simple things
 - same numbers or names in documents
 - often quite effective
- Use of lexicon
 - treat documents as bag of words
 - consider how many words in EN document have translations in FR document



Content Similarity

- Simple things
 - same numbers or names in documents
 - often quite effective
- Use of lexicon
 - treat documents as bag of words
 - consider how many words in EN document have translations in FR document
- A bit more complex
 - semantic representations of documents content
 - bag of word vectors
 - neural network embeddings



Content Similarity

- Simple things
 - same numbers or names in documents
 - often quite effective
- Use of lexicon
 - treat documents as bag of words
 - consider how many words in EN document have translations in FR document
- A bit more complex
 - semantic representations of documents content
 - bag of word vectors
 - neural network embeddings
- Major challenge: do this fast for $n \times m$ document pairs



Google's Content Matching

- Basic idea: translate everything into English, match large n-grams
- For each non-English document:
 1. Translate everything to English using MT
 2. Find distinctive ngrams
 - (a) rare, but not too rare (5-grams)
 - (b) used for matching only
- Build inverted index: ngram → documents

[cat sat on] → {[doc₁, ES], [doc₃, DE], ...}
[on the mat] → {[doc₁, ES], [doc₂, FR], ...}



Matching using Inverted Index

```
[cat sat on] -> {[doc1, ES], [doc3, DE], ...}  
[on the mat] -> {[doc1, ES], [doc2, ES], ...}  
[on the table] -> {[doc3, DE]}
```

- For each n-gram
 - generate all pairs where:
 - * document list short (≤ 50)
 - * source language different
- Result: [doc₁, doc₃], ...



Scoring using Forward Index

- Forward index maps documents to n-grams
- For each document pair $[d_1, d_2]$
 - collect scoring n-grams for both documents
 - build IDF-weighted vector
 - distance: cosine similarity

Scoring Document Pairs

- Given

$$\text{ngrams}(d_1) = n_1, n_2, \dots, n_r$$

$$\text{ngrams}(d_2) = n'_1, n'_2, \dots, n'_{r'}$$

- Inverse document frequency

$$\text{idf}(n) = \log \frac{|D|}{\text{df}(n)}$$

where: $|D|$ = number of documents

$\text{df}(n)$ = number of documents with n

- Scoring of IDF-weighted vectors v

$$v_{1,x} = \text{idf}(n_x) \text{ if } n_x \in \text{ngrams}(d_1), 0 \text{ otherwise}$$

$$v_{2,x} = \text{idf}(n_x) \text{ if } n_x \in \text{ngrams}(d_2), 0 \text{ otherwise}$$

$$\text{score}(d_1, d_2) = \frac{v_1 \cdot v_2}{||v_1||||v_2|||}$$



sentence alignment



Sentence Alignment

- Much early work in 1990s, e.g., Gale and Church (1991)
 - find sequence of 1-1, 1-2, 0-1, etc., sentence alignment groups
 - good element in sequence = similar number of words
 - dynamic programming search for best sequence



Sentence Alignment

- Much early work in 1990s, e.g., Gale and Church (1991)
 - find sequence of 1-1, 1-2, 0-1, etc., sentence alignment groups
 - good element in sequence = similar number of words
 - dynamic programming search for best sequence
- Featurized alignments
 - with dictionary (Hunalign)
 - with induced dictionary (Gargantua)
 - consider tags such as <P>

Sentence Alignment

- Much early work in 1990s, e.g., Gale and Church (1991)
 - find sequence of 1-1, 1-2, 0-1, etc., sentence alignment groups
 - good element in sequence = similar number of words
 - dynamic programming search for best sequence
- Featurized alignments
 - with dictionary (Hunalign)
 - with induced dictionary (Gargantua)
 - consider tags such as <P>
- Sensitive to noise — often large parts of page not translated



Sentence Pair Similarity

- Core Problem: both sentences must have same meaning



Sentence Pair Similarity

- Core Problem: both sentences must have same meaning
- Translate foreign sentence into English
measure similarity with metrics like BLEU



Sentence Pair Similarity

- Core Problem: both sentences must have same meaning
- Translate foreign sentence into English
measure similarity with metrics like BLEU
- Words in one sentence have translation in the other

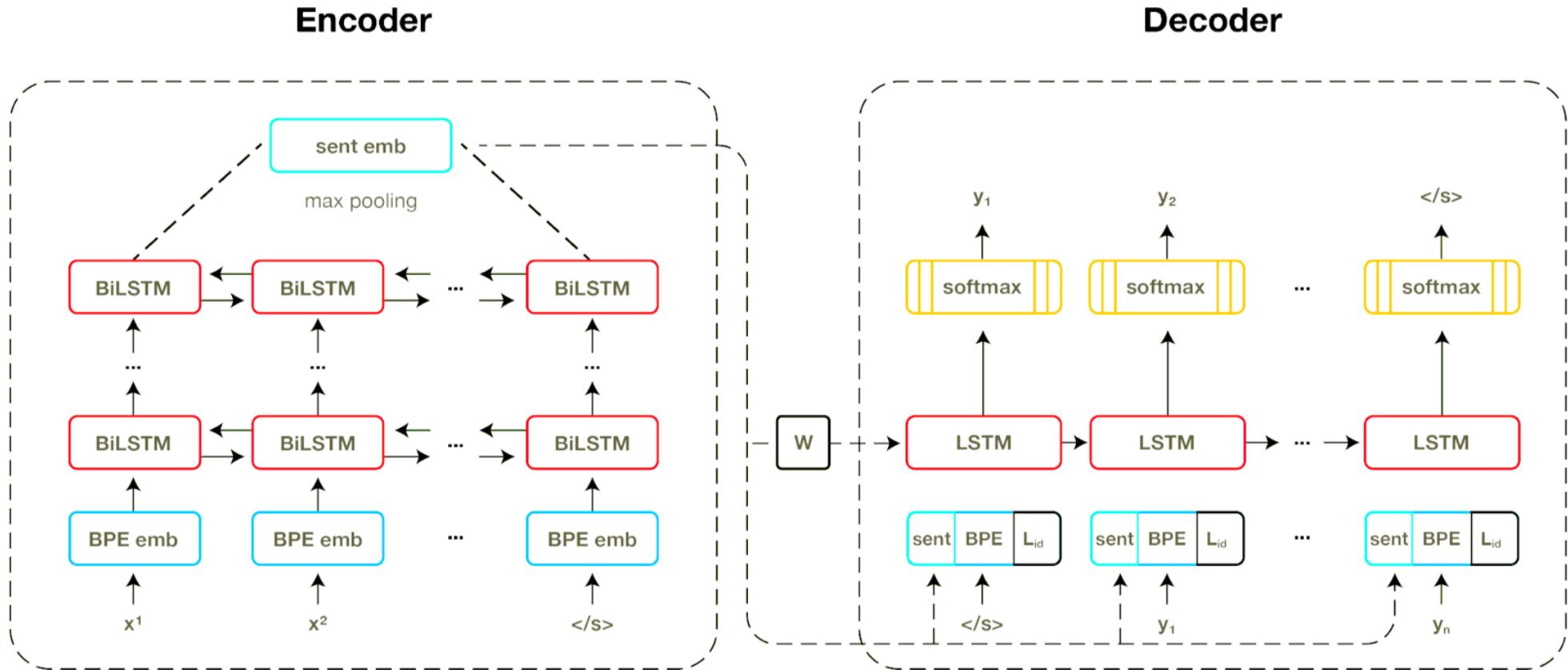


Sentence Pair Similarity

- Core Problem: both sentences must have same meaning
- Translate foreign sentence into English
measure similarity with metrics like BLEU
- Words in one sentence have translation in the other
- Cross-lingual sentence embeddings

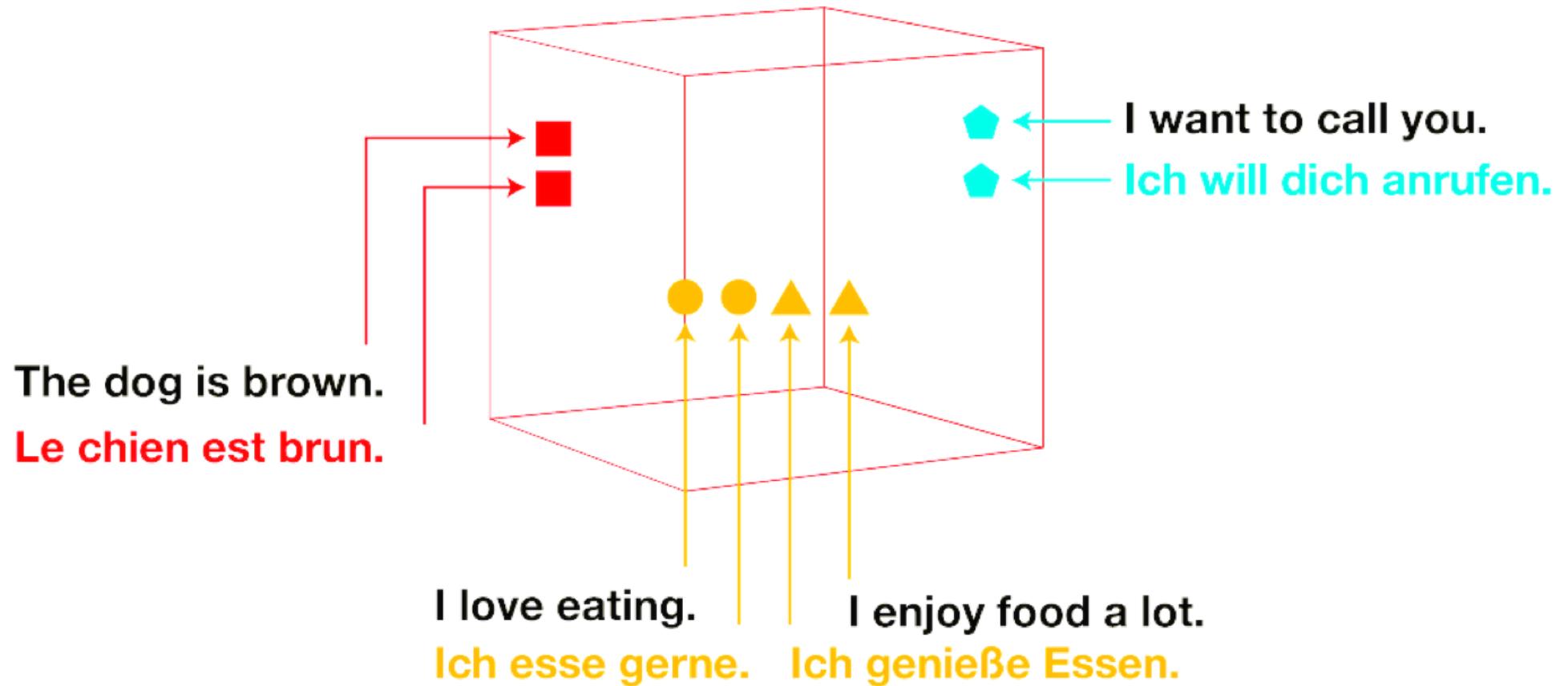


Sentence Embeddings



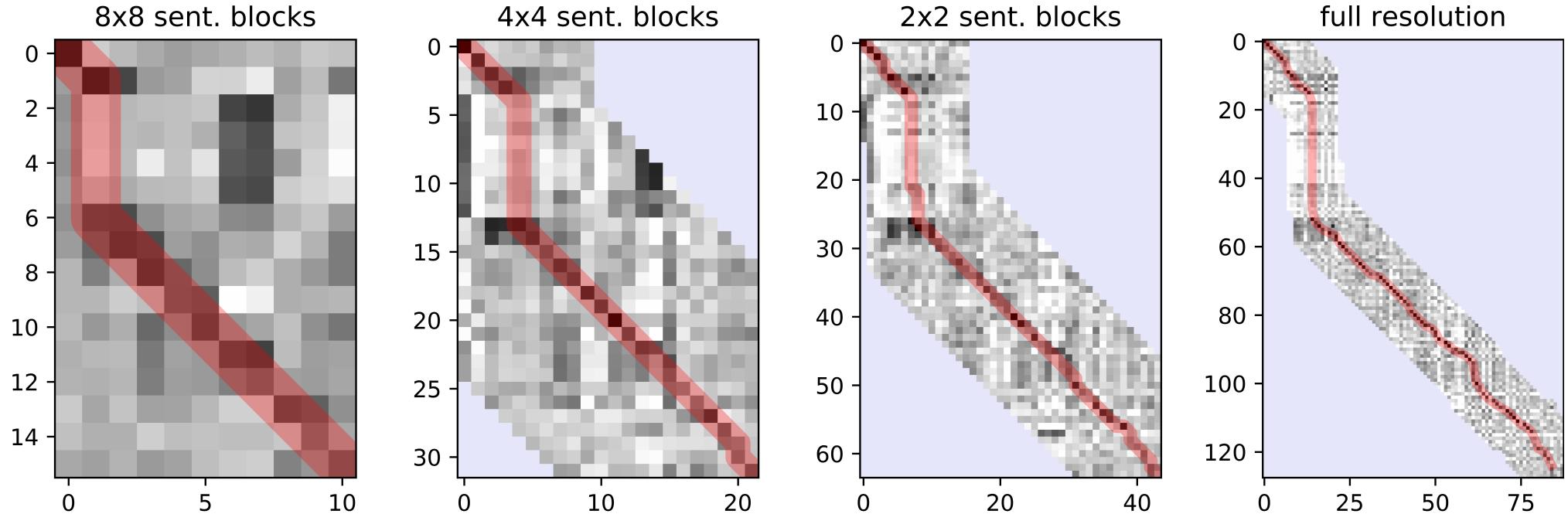
- LASER: Neural machine translation model with bottleneck feature

Sentence Embeddings





Vecalign



- Uses LASER sentence embeddings
- Linear time coarse-to-fine algorithm



sentence pair filtering



Filtering Bad Data

- Mismatched sentence pairs from errors in pipeline



Filtering Bad Data

- Mismatched sentence pairs from errors in pipeline
- Non-literal translation
 - e.g. news stories are notoriously non-literal



Filtering Bad Data

- Mismatched sentence pairs from errors in pipeline
- Non-literal translation
 - e.g. news stories are notoriously non-literal
- Bad translations



Filtering Bad Data

- Mismatched sentence pairs from errors in pipeline
- Non-literal translation
 - e.g. news stories are notoriously non-literal
- Bad translations
- Machine translation
 - much of the parallel text on the Internet generated by Google Translate
 - detection hard — looks like very clean parallel data
 - maybe too clean (little reordering, very literal)
 - watermarking machine translation (Venugopal et al., 2011)



Filtering Bad Data

- Mismatched sentence pairs from errors in pipeline
- Non-literal translation
 - e.g. news stories are notoriously non-literal
- Bad translations
- Machine translation
 - much of the parallel text on the Internet generated by Google Translate
 - detection hard — looks like very clean parallel data
 - maybe too clean (little reordering, very literal)
 - watermarking machine translation (Venugopal et al., 2011)
- How clean should it be?
 - trade-off between precision and recall unclear



Methods

- Dual cross-entropy
 - view sentence pair as input/output
 - score with neural machine translation model in both directions
 - scores should be low and similar



Methods

- Dual cross-entropy
 - view sentence pair as input/output
 - score with neural machine translation model in both directions
 - scores should be low and similar
- LASER embeddings



Methods

- Dual cross-entropy
 - view sentence pair as input/output
 - score with neural machine translation model in both directions
 - scores should be low and similar
- LASER embeddings
- Feature-based approaches
 - matching numbers, named entities
 - language model probabilities
 - lexical translation probabilities

Methods

- Dual cross-entropy
 - view sentence pair as input/output
 - score with neural machine translation model in both directions
 - scores should be low and similar
- LASER embeddings
- Feature-based approaches
 - matching numbers, named entities
 - language model probabilities
 - lexical translation probabilities
- Classifier
 - positive example: sentence pair from clean corpus
 - negative example: corrupted example (misalignment, words changed, ...)



Open Challenges

- Currently serious attempt at broad crawling for parallel data at JHU
- Major challenges
 - crawling (just using standard tool)



Open Challenges

- Currently serious attempt at broad crawling for parallel data at JHU
- Major challenges
 - crawling (just using standard tool)
 - document alignment (major research topic)
 - shared task at WMT 2016 machine translation conference



Open Challenges

- Currently serious attempt at broad crawling for parallel data at JHU
- Major challenges
 - crawling (just using standard tool)
 - document alignment (major research topic)
 - shared task at WMT 2016 machine translation conference
 - sentence alignment (just using standard tool)



Open Challenges

- Currently serious attempt at broad crawling for parallel data at JHU
- Major challenges
 - crawling (just using standard tool)
 - document alignment (major research topic)
→ shared task at WMT 2016 machine translation conference
 - sentence alignment (just using standard tool)
 - detection of machine translated text (some old work)



Open Challenges

- Currently serious attempt at broad crawling for parallel data at JHU
- Major challenges
 - crawling (just using standard tool)
 - document alignment (major research topic)
 - shared task at WMT 2016 machine translation conference
 - sentence alignment (just using standard tool)
 - detection of machine translated text (some old work)
 - filtering out bad sentence pairs (major research topic)
 - shared tasks at WMT 2018–2020 machine translation conference



Open Challenges

- Currently serious attempt at broad crawling for parallel data at JHU
- Major challenges
 - crawling (just using standard tool)
 - document alignment (major research topic)
 - shared task at WMT 2016 machine translation conference
 - sentence alignment (just using standard tool)
 - detection of machine translated text (some old work)
 - filtering out bad sentence pairs (major research topic)
 - shared tasks at WMT 2018–2020 machine translation conference
- JHU efforts (Paracrawl): continuously processing terabytes of data