# The Computable News Project Milestone 7 Production NEL

James Curran

ə-lab School of Information Technologies The University of Sydney





### Computable News team

- Project leader: James Curran
- Project manager: Candice Loxley
- Postdoctoral researchers:
  - Daniel Tse
  - second position still being filled (2 year position)
- Senior Software Developer: Will Cannings
- PhD students:
  - Joel Nothman
  - Will Radford
  - Tim O'Keefe



#### Computable News team

- PhD students on related work:
  - Tim Dawborn
  - Andrew Naoum
  - Glen Pink
- Summer Scholars:
  - Fergus Macpherson
  - Sebastian Pauka
  - Kristy Hughes



# M7: Engineering

- ✓ Supported high-profile Melbourne Cup demo
- ✓ On site support for My Masthead development environment
- ✓ Code cleanup, installation and improved test-case coverage
- Finalised database testing to enable Cassandra decision
- ✓✓ Switched NEL backend to Cassandra
- ✓ Extensive consultation about NEL and Cassandra optimisation
- ✓ Large-scale, fast NEL with Cassandra on over 150 execution hosts



#### M7: NEL

- ✓✓ TAC 2012 full results
  - ✓ Improvement from 72.44 F1 to 73.96
    - More data cleaning
    - Local context features





# M7: Facts & Opinions

- ✓ Preliminary apposition extraction
- ✓ Preliminary slot filling
- ✓ Preliminary numeric fact extraction
- Refined quote-opinion annotation scheme
- ✓ All quotes have at least been double-annotated with opinions
- ✓ Quotes system working in docrep





#### M7: Events

- ✓ Built a corpus of hyperlinks within DCDS data
- Annotated a subcorpus for event links
- ✓ Built a basic classifier to replicate this annotation
- ✓ Zone weighting for hyperlink detection ⇒ 17% relative gain



## M7: Summer Scholarship Programme

- Hired three exceptional students
- ✓ All working on key CompNews problems
- ✓ 12 weeks of engaging research work
  - gives the students a taste of research
  - hopefully gives the students a taste for research
  - gives PhD students supervision experience



### Melbourne Cup demo

- Ported demo timeline to timeline.js
- Integrated new design
- Implemented link scoring to counter crowded timelines
- Prototype tools for curating timelines
- Linked and loaded racing stories
- New type of entity: HORSE





#### Extensive support

- Spent after hours time on site to assist in deploying FP for My Masthead
- As a result of this, we packaged required linking data and created automated installation scripts to simplify deployment
- Contributed to database testing, performance testing, product discussions and code workshops





### Software Engineering

- Trimmed dependencies
- Full-use of python dependency management tools:
  - pip
  - easy\_install
- New prompt-less installation scripts can be used to install FP with no interaction
- Set up VM images simulating the Fairfax architecture for testing





#### Database testing conclusions

- Completed comprehensive read and write testing of Cassandra and Hypertable
- Hypertable was >2x faster at reads, >4x faster at writes
- Because of ops familiarity, Cassandra was selected
- Current low read/write requirements means Cassandra performs acceptably
- Performance will need to be reviewed when counts 2 data is integrated





### Faster linking

- Changing databases presented an opportunity to refactor the linking code
- Linking data is now stored in an optimised, pre-computed format
- Less data is transferred, and the linkers themselves are simplified
- This is less flexible than computing data as needed, but improves linking speed
- Average per-doc speed on a small document set (SMH 2012-01-01) is 1.06s
- Overhead will mean documents linked through the API will take longer than this, but will on average take less than 5s





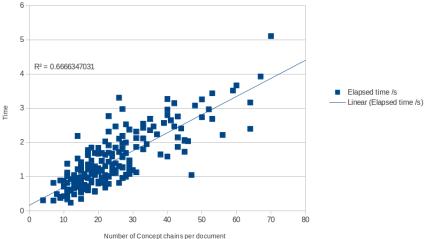
### Batch linking

- During university holidays 157 undergraduate desktop machines are available as a cluster
- A bulk linking queue system was created to utilise this
- Multiple Cassandra and Solr replicas were set up to distribute load
- 1 year of articles (Dec 2011 Nov 2012) from 4 mastheads (SMH, The Age, WA Today and Brisbane Times) were used to test performance
- Linking took 1.95hrs (avg 4.5s per doc on each node), and produced 15.8gb of data





### Number of concepts determines document linking speed





#### Consolidating TAC 2012 success

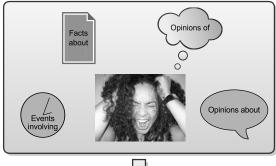
- Wrote and submitted system description paper
- Early access to other system description papers
- We are ranked #2 3.1% off the pace for KB linking

Team	кв В <sup>3+</sup>
Microsoft Research	68.7
CMCRC	65.6





# Characterising entities









#### What do we know about our entities?

- News includes facts about entities to give the reader context
  - age
  - job description
  - spouse
  - stock ticker
  - ...
- We want to extract facts and use them for
  - · improving linking accuracy
  - building a knowledge base
  - automatically enriching news





# Apposition, a structure for adding information, ...

 Readers need to understand a story's context, but some entities require extra work on behalf of the journalist

#### Ambiguous entities

Hey Dad! star Robert Hughes will plead not guilty ...

#### Novel entities

His lawyer, Greg Walsh, says . . .

- Apposition relates a **head** Noun Phrase with one or more coreferent attribute Noun Phrases
- Punctuation is a reasonable cue, but not a silver bullet





## Apposition for Named Entity Linking

- Precise, local and strong attributes are well-suited to NEL
- Can apposition help
  - disambiguate known concepts?
  - disambiguate unknown concepts (i.e., two "John Smiths")?
  - ullet extract enough textual information for fast, database NEL?

```
SELECT concept
WHERE name = 'Robert Hughes'
AND role = 'actor'
```





## Finding person appositions

- Using sentence context (a rough approximation) increases performance from 71.41 to 73.96
- We have simple patterns over POS and NER tags.

#### HEAD, ATTR,

Ntaras, a trained cage fighter, ...

#### ATTR, HEAD,

The victim, 19-year-old Nicholas Barsoum, ...

• We plan to incorporate apposition detection into NEL





## Extracting facts for Slot Filling

- Apposition is highly specific and is narrow coverage
- Slot filling involves extracting named facts about specific entities
- This requires identifying
  - Entities (i.e., NEL)
  - Values (this can require inference)
  - Value types (including normalisation)
  - Slots those values fill
  - Resolving duplicate or conflicting slot values





#### Slot filling

#### Place and date of birth

Robert Hughes was *born* in Sydney on July 28, 1938 into a prominent family of lawyers and politicians.

#### Age, knowing that the article was published 21/11/2012

... signed an extradition order for <u>Hughes</u> after a London magistrate in September determined that the <u>64</u>-year-old return to NSW for questioning.





#### Slot filling

#### Number of employees or members

...lauded by the <u>American Psychiatric Association</u>, which *represents* more than 36,000 physicians ...

#### Employment history

Assigned to the Domestic Relations Court, later renamed Family Court, Bolin fought racial discrimination . . .





## Kristy's project: Extracting numerical facts from news

- ✓ Identify and normalise numeric and date values
  - "... was forced to inject 183.5 million dollars into Aerolineas this year to keep it operating and pay its 9,000 employees."
  - "... was forced to inject 18350000 dollars into Aerolineas 2012 to keep it operating and pay its 9000 employees."
  - Next step is to identify the type and slot each value fills

Slot	Type	Value
Investment	DOLLARS	183500000
Event time	YEAR	2012
Number of employees	NUMBER	9000





## Quote-based opinion mining

- Traditionally sentiment analysis has involved finding spans of text and labelling them as either positive or negative
- Sometimes this makes sense, e.g. positive about the carbon tax
- Other times it doesn't, e.g. positive about climate change
- What we really want are expressions of a point of view
- · We aim to find quotes that represent different opinions

#### A more complex point of view

"However, the political feasibility of all countries agreeing to a harmonised carbon tax to achieve this outcome is highly questionable"





#### Creating the data

- Getting agreement on what constitutes an opinion is very difficult
- Others have addressed this with lots of annotator training (approx. 40 hrs per annotator)
- We consider disagreement to be natural for this task
- All quotes have been double-annotated and should be triple-annotated by early next week
- Corpus statistics:
  - 700 documents covering 7 topics
  - 3141 quotes, average of 4.5 per doc
  - Estimated final cost for external annotators is \$1200 (approx. \$0.85 for an annotator to complete a doc)





## Modelling event references as links

- We can learn from some hyperlinks in Fairfax stories:
  - The body ... was found under a plastic sheet ....
  - ...that the global hacking incident won't affect them.
  - ... 29-year-old Andy Marshall died this week after ...
  - Ellison was last year named best-paid executive
- and less so from others:
  - ...the Mitsubishi i-MiEV, which is now on sale...
  - Read our previous Brisbane's Best: <u>CBD lunches for \$10 | Chips Bakery | Mexican | Pizza</u>
  - ...according to the QS World University Rankings.
- We can filter some of these out with basic rules:
  - hyperlink density, punctuation, ...





### How can we predict hyperlink targets?

- Baseline: search archive with query = hyperlink anchor context
- Hypothesis: higher weight for target sentences with new content
- We index different portions of each article, such as:
  - Story text
  - Story title
  - First sentence
  - Sentences containing "yesterday", etc.
  - More sophisticated approaches...
- Learn from existing hyperlinks how to weight these "zones"
- So far this yields 17% relative MRR gain





### Concept timelines need to be selective

We can produce a list of documents mentioning Julia Gillard



But which are the most important to show on a timeline?





### Fergus's project: Choosing the best stories for a timeline

- Baseline approaches:
  - Cluster stories by text and timestamp, and choose a representative from each cluster
  - Borrow techniques from summarisation to select key stories
    - Use concept relevance scores to distinguish stories where Gillard is central or peripheral
- We would like to compare news stories to Wikipedia...

```
1 Early life and career
2 Politics
3 Member of Parliament
3.1 Shadow Cabinet
3.2 Deputy Leader of the Opposition
4 Deputy Prime Minister
5 Prime Minister
5.1 Gillard replaces Rudd
5.2 2010 election
5.3 Domestic policies
5.3.1 Health
```





#### Processing historical news

- Our extracted information enhances the future and the past.
- Four collections of Fairfax data:
  - DCDS (2008–present)
  - FutureTense (2002–2009)
  - NewsStore (1986–2009)
  - Microfiche via Google OCR (1830–1989)
- We would like to process these seamlessly.





#### Towards a unified archive

- We can store the digitised texts in a unified format.
- Statistical models are best without duplicates:
  - We intend to implement automatic deduplication
  - Fairfax should provide any known duplicate IDs





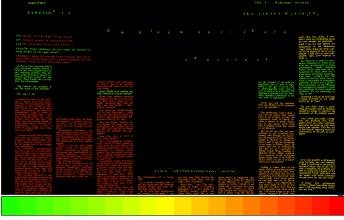
# Sebastian's project: Cleaning and ordering OCR output

- Segmenting images into logical segments (paragraphs, headings, bylines, etc.) to extract page features and reading order.
- This will enable us to extract individual articles from pages
- Google OCR data does not adequately group together contiguous segments of the page
- Our segmentation identifies paragraph and image segments reasonably well
- Next step: NLP on noisy text (Andrew's PhD)





# Colour shows position in Google-generated HTML file





James Curran

### Current segmentation progress



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#### Supporting news timeline

- Store NEL data
- Check API calls
- Link and load 5-10 years or articles
- Link and load available photo and video assets





# Improving linking performance with journalist feedback

F1	Method
n/a	Baseline: use only Wikipedia statistics
70.98	Train an NER model for SMH-specific expression of names
73.96	Use concept-mention cooccurrence statistics to bias to-
	ward commonly observed links from SMH articles

#### Further directions

- Concept-concept cooccurrence to bias toward concepts that occur together (requires count2 data)
- Learn a statistical model for NEL





#### Batch annotation and correction

 TODO: DT: we mentioned this last meeting, but nothing since

