GATE and Social Media: Named entities

Dom Rout
Kalina Bontcheva
Leon Derczynski (slides)

Entity mining

Texts frequently focus on particular entities

To discover what documents say about them, we can:

- Recognise entity mentions
- Disambiguate entities to external vocabularies
- Find opinions that authors have about the entities

Important:

- Enables IE over tweets
- Critical for event extraction (actors, events)
- Describes the topic of the tweet

Tough:

- ANNIE doesn't do well – around 50% F1
- Stanford's leading tool does even worse – around 40% F1!

What's going on? How can we build a tweet NER tool?

NER Intro

- We know social media is more diverse than canonical news text
- We've browsed through entities in tweets
- What practical issues are there in twitter NER?
- What solutions have been proposed?

Named entity recognition: example

Goal is to find mentions of entities

Newswire

London Fashion Week grows up – but mustn't take itself too seriously. Once a launching pad for new designers, it is fast becoming the main event. But LFW mustn't let the luxury and money crush its sense of silliness.

Social media

Gotta dress up for london fashion week and party in style!!!

Named entity recognition: example

Person mentions in news

Left context	Match	Right context
in dicated Atef, including	Douglas Feith	, the United States defence
, the group that killed	President Sadat	in 1981 as retribution for
. The current leader,	President Olusegun Obasanjo	, who recently came to
Kuwait, whose information minister	Sheikh Ahmed Fahed al-Sabah	met editors of local newspapers
The current defence minister,	Theophilus Danjuma	, has also been threatened
The three right-wing MPs,	Andrew Rosindell	(Romford), Andrew
Late on Wednesday night,	Justice Oputa	, who chairs the commission
the militarily-manoeuvred civilian elec...	President Obasanjo	in 1999 and is widely
after the mysterious death of	General Sani Abacha	in 1998.
have learnt that one of	Bin Laden	's closest and most senior
evidence confirms the involvement of	Osama bin Laden	in those attacks."
. He is one of	Bin Laden	's two most senior associates
for future civilian office.	General Buhari	took power in a 1983
$5m price on	Atef	's head and prosecutors have
Afghanistan. He was once	Bin Laden	's chief media adviser and
thinking in the Tory party	Iain Duncan Smith	has ordered three Tory MPs
club and the party,	David Maclean	, the Tory Chief Whip
Centre and the Pentagon.	Mohammed Atef	, who is thought to
are still very powerful.	General Babangida	supported the militarily-manoeuvred civ
sexual orientation or religion.	Mr Duncan Smith	's purge of the Monday
," he said.	Atef	, who is reported variously
of the late singer,	Fela Kuti	� which took place while
field in Penn sylvania.	President Bush	included Atef in an order
. It is believed that	Mr Duncan Smith	intended to launch his crackdown

Named entity recognition: example

Person mentions in tweets

Left context	Match	Right context
i was your age ,	spencer	from iCarly was Crazy Steve
iCarly was Crazy Steve ,	Carly	was Megan and Josh was
bath , shut up ,	sam	's coming tomorrow and steve
. All are welcome ,	joe	included
. All are welcome ,	joe	included
teachers , chinese takeaways ,	gatt holly	, phil collins , the
takeaways , gatt holly ,	phil collins	, the skin of a
@GdnPolitics : RT AlJahom :	Blair	: " I'm gonna
Empls of the Month :	Deborah L	#Speech #Pathologist-Childrens
be the next Pope "	Brown	: " I won't
(via POPSUGAR)	Sarah Jessica Parker	and Gwen Stefani Wrap Up
and is smexy !!;)And	Chelsea Handler	is hilarious ! Finally got
him befnrjustthen about	kenny	signing his book but it
three kinds of reactions after	Ayodhya	verdict .
, Carly was Megan and	Josh	was fat . #damnteenquotes
sam 's coming tomorrow and	steve	and tanya will be round
coming tomorrow and steve and	tanya	will be round at 10am
photo caption contest- Nadal and	Novak	in the tub http://ow.ly/2G3Jh
) Sarah Jessica Parker and	Gwen Stefani	Wrap Up Another Successful New
#Pathologist-Childrens Rehab and	Patricia M	#Referral/#Auth #
Just casually stalking Cheryl AND	Dermot	tomorrow .... NO BIGGIE
did tweet him befnr	justthen	about kenny signing his book
Test : We just congratulated	Lindsay	an hour ago on h
the funny photo caption contest-	Nadal	and Novak in the tub

Named entity recognition: resources

UW (Ritter, 2011)

- 34k tokens, 1500 entities
- Single annotator
- Ten entity types: PERSON, GEO-LOCATION, COMPANY, PRODUCT, FACILITY, TV-SHOW, MOVIE, SPORTSTEAM, BAND, and OTHER

UMBC (Finin, 2010)

- 7k tokens, 500 entities
- Multiple annotator
- Three entity types: PERSON, LOCATION, ORGANISATION

MSM2013 (Basave, 2013)

- 30k tokens, 1500 entities
- Multiple annotator
- Three entity types: PERSON, LOCATION, ORGANISATION
- Hashtags, URLs and entities obfuscated

Named entity recognition: issues

Genre differences in entity type

	News	Tweets
PER	Politicians, business leaders, journalists, celebrities	Sportsmen, actors, TV personalities, celebrities, names of friends
LOC	Countries, cities, rivers, and other places related to current affairs	Restaurants, bars, local landmarks/areas, cities, rarely countries
ORG	Public and private companies, government organisations	Bands, internet companies, sports clubs

Named Entity Recogntion Structure

Design choices in NER: (Roth 2009)

- **What feature representation to use for tokens;**
- **Which inference algorithm to use;**
- **How to capture non-local dependencies;**
- **How to incorporate external knowledge.**

Representation and labeling

Token feature representation options:

- Token itself
- Previous and following token
- Word shape, to model capitalisation
- Lexical features (e.g. character n-grams) to help with OOV terms
- Part of speech tag
- Parsing information
- Word embeddings
- Word sense clusters

NER inference algorithms

As with part of speech tagging, sequence labelling can work well (e.g. CRF)

- Assumes well-formed sentences and lots of training data
- If this is inappropriate, then local context in token features can compensate

Representation and labeling

Labelling scheme:

I	Facebook	B-company
O	Job-Hunting	O
O	App	O
I	BranchOut	B-product
O	Raises	O
O	$6	O
O	Million	O
O	From	O
I	Accel	B-company
O	And	O
I	Super	B-company
I	Angels	I-company

BIO (Begin, In, Out) allows separation of adjacent entities

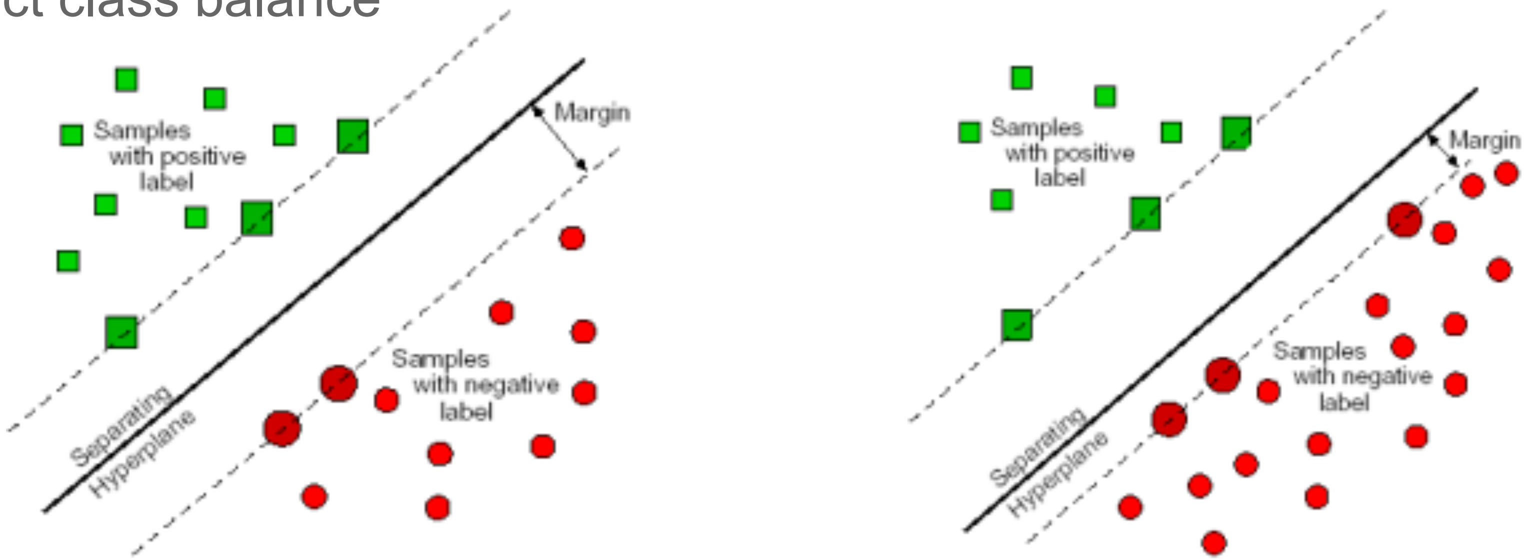
CRF with BIO popular

SVM-U with IO can give better performance

Representation and labeling

SVM-U: “uneven” (Li 2009)

Adjust margins between supporting examples and decision hyperplane to reflect class balance



Well-suited to tasks like NER, where one class is much more frequent than another

Retains SVM's advantage of being noise-resistant

Dependencies & external knowledge

Typically, only the first mention of an entity is referred to in full:

> Manchester United are great. They're my favourite football team. Man U forever!

Using only local features will lead to missed entities.

Tweets are not long discourses

- Possible for the long first mention to be missing
- Include context from elsewhere

How can we incorporate external knowledge for NER?

- Useful for unusual/unexpected words in an entity: “Szeged” “White House”

Dependencies & external knowledge

Unlabelled text

- NEs found in distributionally similar contexts
- Labelled LDA can produce phrase lists given an entity type (Ramage 2009, Ritter 2011)

Gazetteers

- Can be constructed manually or automatically
- Gaz. completeness gives P/R tradeoff
- Won't catch terms not seem in gazetteer, which makes domain adaptation tough

Named entity recognition approaches

Ritter (2011) addresses named entity recognition in tweets using a data-intensive approach

Distinct segmentation and classification tasks

- Discriminative segmentation
- Distantly supervised classification

Assume that @mentions are unambiguous

Found that inclusion out-of-domain data (from MUC) actually reduces performance

Named entity recognition approaches

Models entity segmentation as sequence labeling using BIO representation and CRF

- Orthographic, contextual features
- Dictionary features based on type lists in Freebase
- Brown clusters from PoS tagging, NP/VP/PP chunking, capitalisation

Segmentation outperforms default Stanford NER consistently

- Stanford: F1 44%
- Segmentation without clusters: F1 63%
- Segmentation with clusters: F1 67% (52% error reduction)

Named entity recognition approaches

After segmentation, Ritter (2011) describes NE classification

- Diversity in entity types exacerbates data sparsity problem
- Lack of context makes classification difficult even for humans
- e.g., KKTNY in 45min..........
- Co-occurrence can help in situations like this (Downey 2010)

Named entity recognition approaches

Exploiting co-occurence information with LabeledLDA and Freebase

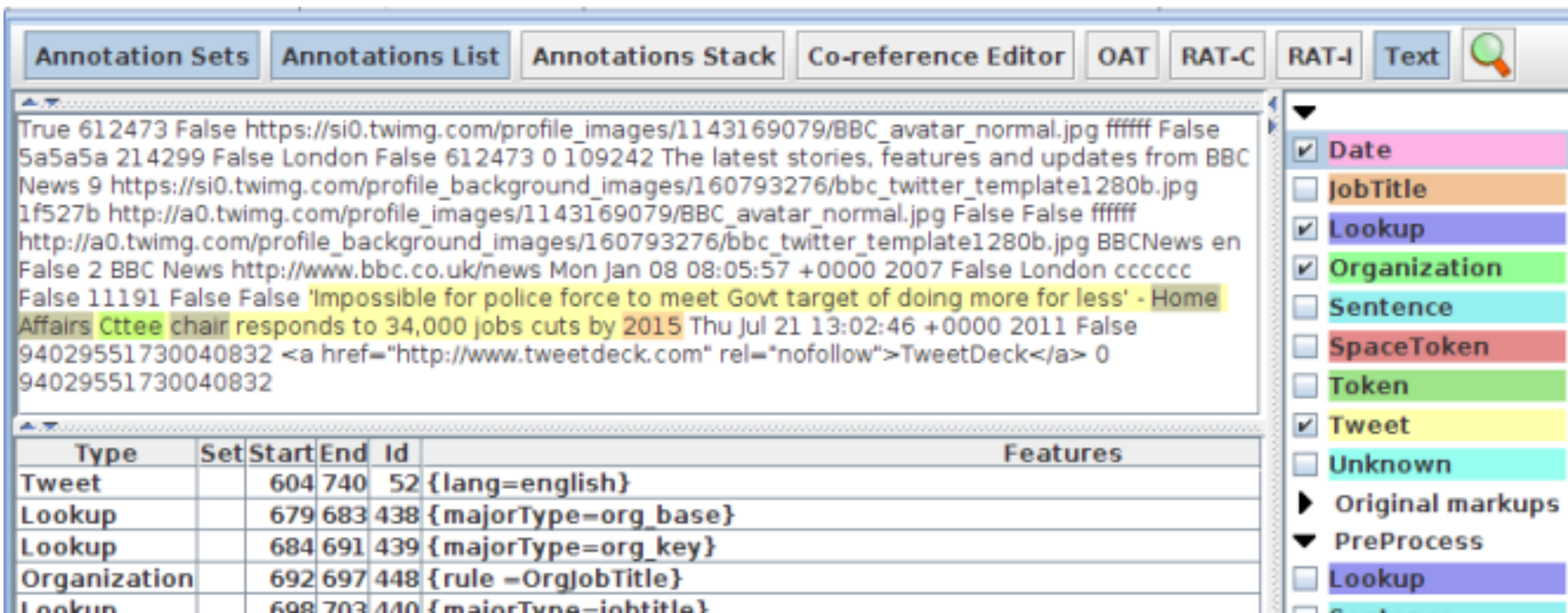
- Freebase provides type ontology
- LabeledLDA assigns distribution of potential Freebase types to entity mentions
- Entity mention context modelled as bag-of-words
- Distribution can vary from mention to mention
- Include prior for type distribution θ_e from encountered examples, to compensate for cases where there are few words for context

Evaluation over 2400 tweets, 10 types

- Unlabelled data from 60M NE segmented tweets (24K distinct entity strings)
- Freebase F1 38%
- Supervised F1 45% (MaxEnt)
- LabeledLDA F1 66%

ANNIE NER on Tweets

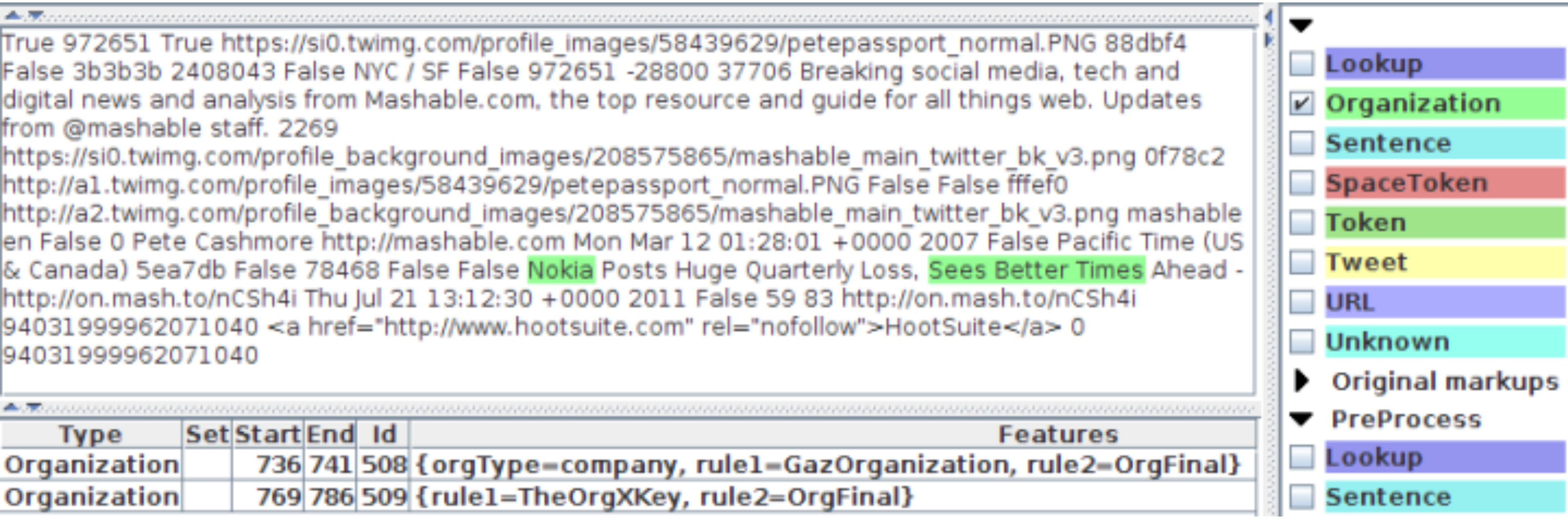
- To run the ANNIE Transducer just on the tweet text:
  - Create and add an ANNIE Gazetteer and add it
  - Instantiate an ANNIE NE Transducer PR with defaults
  - Add it to the end of your application
  - Run it and inspect the default annotation set for NEs

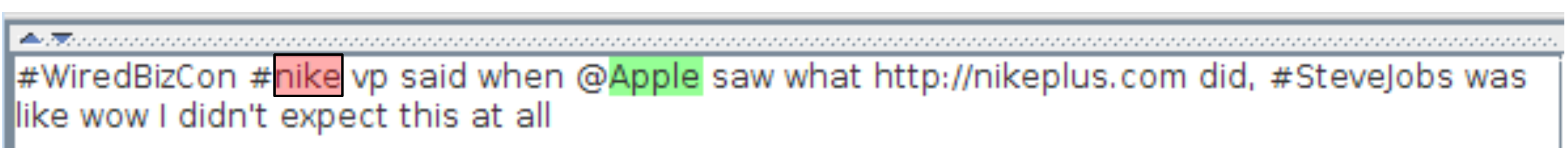


Why the mistake? OrgJobTitle rule

```
Rule: OrgJobtitle
Priority: 30
(
 {Unknown.kind == PN}  //It is only considering one preceding word as a candidate
                       //Grammar in plugins/ANNIE/resources/NE/org_context.jape
):org
(
 {Lookup.majorType == jobtitle}
)
-->
 {
    gate.AnnotationSet org = (gate.AnnotationSet) bindings.get("org");
    gate.FeatureMap features = Factory.newFeatureMap();
    features.put("rule ", "OrgJobTitle");
    outputAS.add(org.firstNode(), org.lastNode(), "Organization",
                      features);
    outputAS.removeAll(org);
}
```

Tweet Capitalisation: an NER nightmare!





…And hashtag semantics is yet another…

Case-Insensitive matching

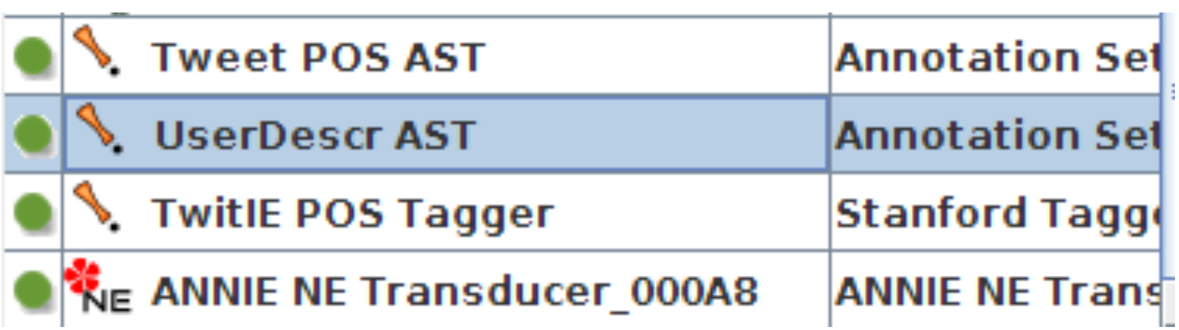
- This would seem the ideal solution, especially for gazetteer lookup, when people don't use case information as expected
- However, setting all PRs to be case-insensitive can have undesired consequences
  - POS tagging becomes unreliable (e.g. “May” vs “may”)
  - Back-off strategies may fail, e.g. unknown words beginning with a capital letter are normally assumed to be proper nouns
  - BUT this doesn’t work on tweets anyway!
  - Gazetteer entries quickly become ambiguous (e.g. many place names and first names are ambiguous with common words)
- Solutions include selective use of case insensitivity, removal of ambiguous terms from lists, additional verification (e.g. use of the text of any contained URLs)

More flexible matching techniques

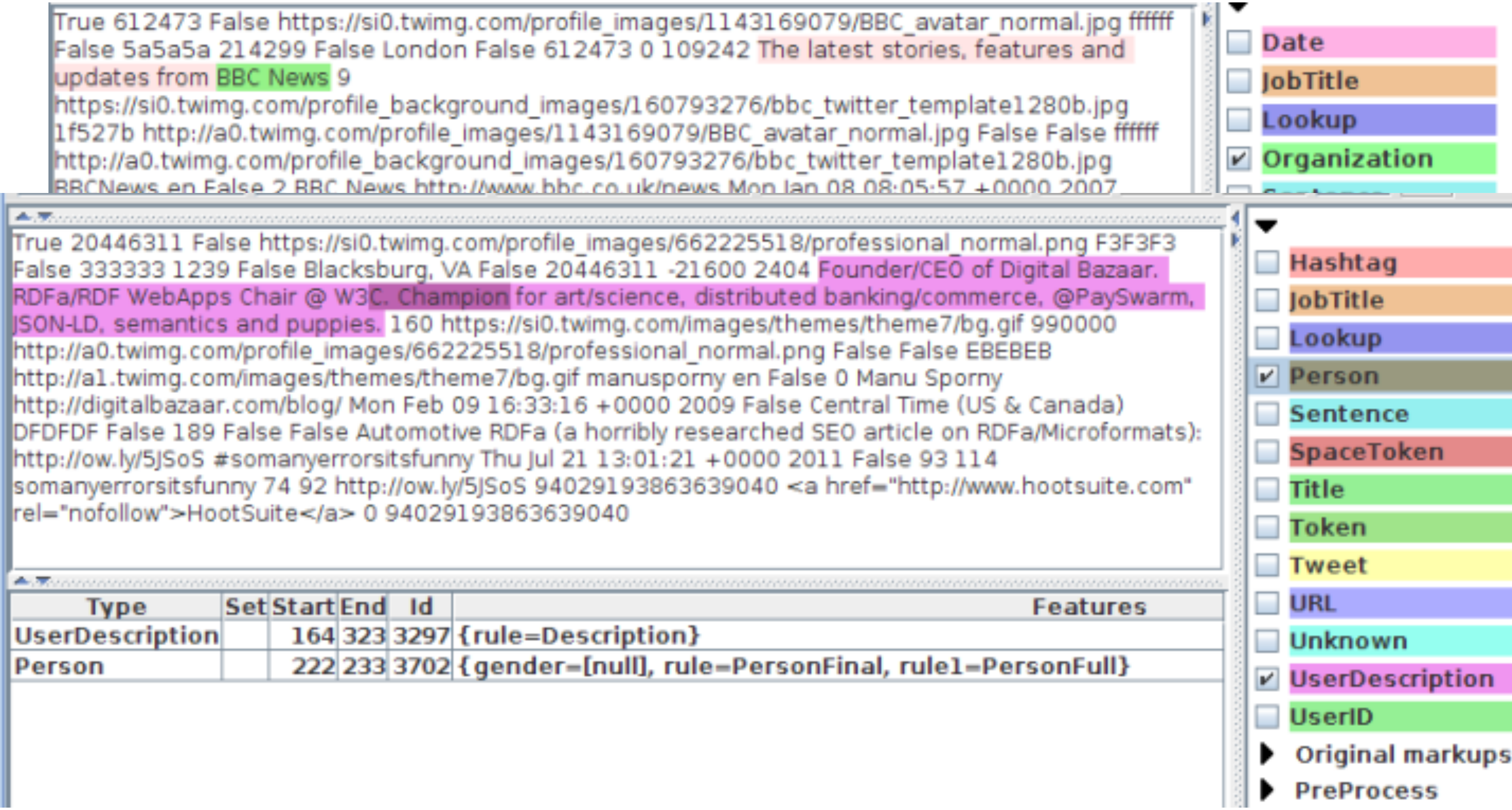
- In GATE, as well as the standard gazetteers, we have options for modified versions which allow for more flexible matching
- BWP Gazetteer: uses Levenshtein edit distance for approximate string matching
- Extended Gazetteer: has a number of parameters for matching prefixes, suffixes, initial capitalisation and so on

Try: Run ANNIE on User Profile Text

- User descriptions are another piece of useful text to mine
- Appear as UserDescription annotations in PreProcess
- Create another Annotation Set Transfer from PreProcess to the default set, using the UserDescription annotation from PreProcess as the textTagName
  - HINT: See the parameters of the Tweet POS AST
- Add the new AST PR after the Tweet POS AST, but before the TwitIE POS Tagger. Re-run the app



ANNIE Results in User Descriptions



…TwitIE NE rules are being improved, watch this space…

Hands-on: NER

Let's measure ANNIE performance on social media text

We'll run this over the Ritter-dev corpus, from r-tweets, so if you don't have this open, you can open it from the datastore saved in corpora/r-tweets

Run your pipeline, including the ANNIE NE trandsucers, on this corpus

Open the corpus and click the “Corpus Quality Assurance” tab

We want to compare Original Markups, the key, with the default annotations, the response

Select annotation types of Location, Organization, and Person

Pick an evaluation measure

How does it do? What kinds of errors are most prevalent, missed or spurious?

You can also pick individual documents and see which single annotations are picked up or missed

Named entity recognition summary

Named entity recognition in tweets is hard

Three major classes of Tweet NER approach:

- Sequence labelling – like Stanford CRF chunker
  - Problem: tweets aren't well-formed enough
  - Problem: lack of training data
- Lookup-based using local grammar and string matching
  - Problem: strings are often misspelled
  - Problem: entity mentions aren't in gazetteers (drift) (Eisenstein 2013, Plank 2014)
  - Advantage: cuts through linguistic noise, agnostic to many style variations
- Grouding to vocabulary (e.g. Dbpedia)
  - Problem: insufficient context to disambiguate
  - Problem: entities often appear in social media before the resource

Overall solutions to twitter noise

Normalisation

- Convert twitter text to “well-formed” text; e.g. slang resolution
- Some success using noisy channel model (Han 2011)
- Techniques include: edit distance; double metaphone with threshold
- Issues: false positives can change meanings, e.g. reversing sentiment (apolitical)

Domain adaptation

- Treat twitter as its own genre, and create customised tools and techniques
- Some success in language ID (Carter 2013), PoS tagging (Gimpel 2011), NER (Ritter 2011)

Flexible representations

- Represent document text in a way that is resilient to noise
- Brown clustering, word embeddings, deep learning