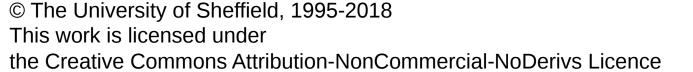


Module 3: GATE and Social Media

3: TwitlE components





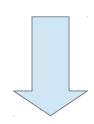
University of Sheffield, NLP

NLP Pipelines



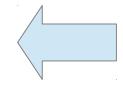






Text









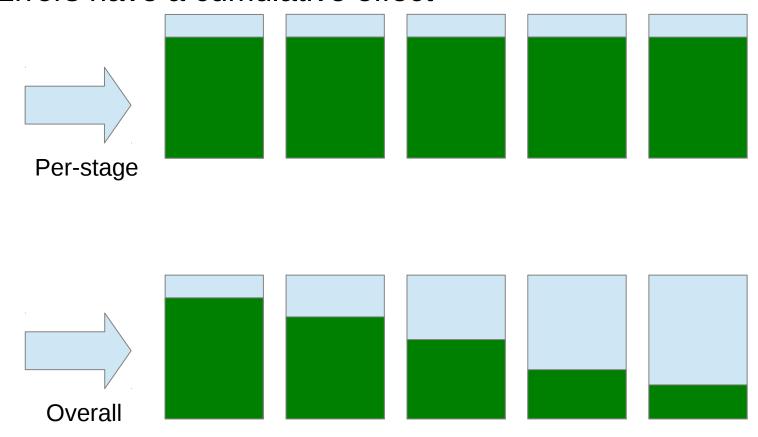
Part of speech tagging

Tokenisation

Pipelines for tweets



Errors have a cumulative effect



Good performance is important at each stage

Language ID: example



Task: given a text, determine which language it is in

Newswire:

The Jan. 21 show started with the unveiling of an impressive three-story castle from which Gaga emerges. The band members were in various portals, separated from each other for most of the show. For the next 2 hours and 15 minutes, Lady Gaga repeatedly stormed the moveable castle, turning it into her own gothic Barbie Dreamhouse.



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Twitter:

LADY GAGA IS BETTER THE 5th TIME OH BABY(:

je bent <u>Jacques cousteau</u> niet die een nieuwe soort heeft ontdekt, het is duidelijk, ze bedekken hun gezicht. <u>Get over it</u>

I'm at <u>地铁望京站</u> Subway <u>Wangjing</u> (<u>Beijing</u>) http://t.co/KxHzYm00

RT @TomPIngram: VIVA LAS VEGAS 16 - NEWS #constantcontact http://t.co/VrFzZaa7

Language ID: issues



Accuracy on microblogs: 89.5% (Preotiuc-Pietro 2012)

Accuracy on formal text: 99.4% (Carter 2013)

What general problems are there in identifying language in social media?

- Switching language mid-text;
- Non-lexical tokens (URLs, hashtags, usernames, retweet/modified tweet indicators);
- Small "samples": documents are fixed at 140 characters, and document length has a big impact on language identification;
- Dysfluencies and fragments reduce n-gram match likelihoods;
- Large (unknown) number of potential languages, some for which there will be no training data (Baldwin 2010).

Social media introduces new information



Metadata:

spatial information (from profile, from GPS); language information (default English is left on far too often).

Emoticons:

```
:) vs. ^_^
```

cu vs. 88

Language ID: solutions



Carter et al. (2013) introduce semi-supervised priors to overcome short message problems:

- Author prior, using content of previous messages from the same author;
- Link prior, using text from any hyperlinks in the message;
- Mention prior, based on the author priors of other users mentioned in the message;
- Tag prior, gathering text in other messages sharing hashtags with the message;
- Conversation prior, taking content from messages in a conversation thread.

These priors individually help performance

- Author prior offers 50% error reduction, and is most helpful in five languages surveyed.
- Why? This prior will generate the most content the others are conditional.

Language ID: solutions (2)



Combining priors leads to improved performance

- Different strategies help for different languages;
- Tried: voting, beam search, linear interpolation, beam confidence, lead confidence.
- Beam confidence (reducing prior weight when many languages close to most likely).

Tricky cases remain difficult, especially when languages mix

 Fluent multilingual posts; foreign named entities; misleading priors; language ambiguous

Language ID: solutions (3)



Carter technique can be demanding

- Data may not be available: API limits, graph changes, deleted items, changed web pages
- Processing time: retrieving required information is slow
- Privacy concerns: somewhat invasive

Lui and Baldwin (2012) use information gain-based feature selection for transductive language ID

- Goal is to develop cross-domain language identification
- In-domain language identification is significantly easier than cross-domain
- Social media text is more like a mixture of small/personal domains than its own domain

Language ID: solutions (4)



The variety of data and sparsity of features makes selection important

- LD focuses on task-relevant features using information gain
- Features with a high LD score are informative about language, without being informative about domain
- Candidate features pruned before applying LD based on term frequency

Without training, the langid.py tool does better than other language ID systems on social media

- Consistent improvement over plain TextCat, LangDetect and CLD
- Limited to no training data available for the 97 target languages

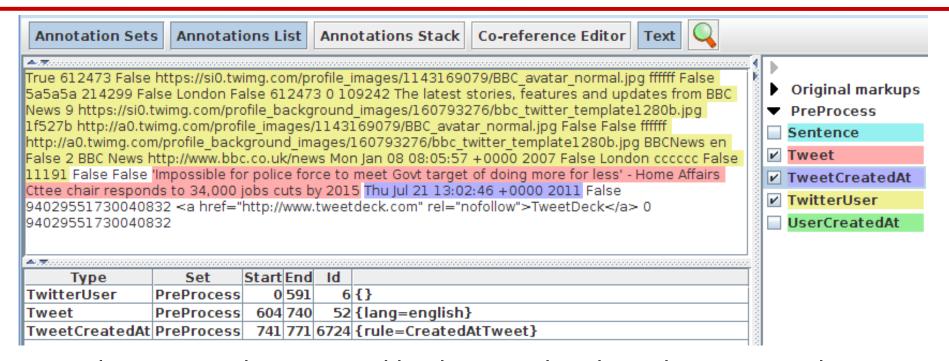
Hands-On 1: Language ID



- Load twitie-lang-id.xgapp in GATE (Restore Application From File)
- Create a new corpus, save to a serial datastore
- Load lang-id-test-tweets.xml:
- Choose Populate from single file, set root element to doc_root
- Run the application
- The Annotation Set Transfer first copies the text annotation from the "Original markups" set as a Tweet annotation in the PreProcess annotation set
- The Tweet Language Identification PR adds a "lang" feature to the Tweet annotation in the PreProcess set
- Inspect the results
- Keep the app open for later, but close the corpus

Language ID Results: English Example





- Various annotations created by the metadata-based pre-processing jape (tweet-metadata-parser.jape in resources)
- Sentence is an annotation created to span the entire tweet text
- TwitterUser spans the entire user information in the tweet
- TweetCreatedAt the timestamp of this tweet

Tokenisation: example



General accuracy on microblogs: 80% Goal is to convert byte stream to readily-digestible word chunks. Word bound discovery is a *critical* language processing task

Newswire:

The LIBYAN AID Team successfully shipped these broadcasting equipment to Misrata last August 2011, to establish an FM Radio station ranging 600km, broadcasting to the west side of Libya to help overthrow Gaddafi's regime.

Twitter:

RT @JosetteSheeran: @WFP #Libya breakthru! We move urgently needed #food (wheat, flour) by truck convoy into western Libya for 1st time:D

@ojmason @encoffeedrinker But it was #nowthatcherisdead that was confusing (and not just to non-UK people!)

RT @Huddy85 : @Mz_Twilightxxx *kisses your ass**sneezes after* Lol

Ima get you will.i.am NOTHING IS GONNA STAND IN MY WAY =)

Tokenisation: issues



Social media text is generally not curated, and typographical errors are common Improper grammar, e.g. apostrophe usage:

```
doesn't \rightarrow does n't doesnt \rightarrow doesnt
```

Introduces previously-unseen tokens

Smileys and emoticons

```
I <3 you \rightarrow <u>I & It</u>; <u>you</u>
This piece ;,,( so emotional \rightarrow <u>This piece</u> ;,, ( <u>so emotional</u>
```

Loss of information (sentiment)

Punctuation for emphasis

```
*HUGS YOU**KISSES YOU* → * HUGS YOU**KISSES YOU *
```

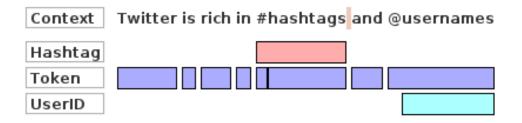
Words run together / skip

I <u>wonde</u> <u>rif</u> Tsubasa is okay..

Tokenisation: solutions



- •We extend the Penn Treebank tool with twitter adaptations
- •Layer multiple annotations on top of each other: Hashtags, Usernames



- Normalisation maps frequent nonstandard spellings to standard
- Via lookup dictionary (e.g. Han 2011); e.g. gonna → going to
- Regular expressions for known smileys/emoticons to avoid splitting them
- Segmenting individual hashtags is possible (Maynard 2014)

```
#openaccess \rightarrow # open access #palmoil \rightarrow # palm oil
```

Hashtag analysis can be tricky GATE



Even for humans!

- #nowthatcherisdead
- #powergenitalia
- #lesbocages
- #molestationnursery
- #teacherstalking
- #therapist









What do these hashtags mean?

- #kktny
- #fomo
- #jomo
- #ootd
- #wcw

Hands-On: Hashtag and @mention tokenisation

- Load a Document Reset and Unicode Tokeniser
- Create a new application and add these to it (Reset first)
- •Create a new corpus, name it "Tweets" and use the "populate from JSON" right-click option (you need the Format: JSON plugin loaded), with the file energy-tweets.json setting the mime type to "text/x-json-twitter"
- •Run the application and look at the Token annotations in the Default annotation set
- Create a JAPE transducer, loading resources/hashtag.jape
- •Add it to the application and re-run. Hashtag annotations appear
- •Now add a new rule to detect @mentions as UserID annotations (don't forget to re-initialise the JAPE transducer)

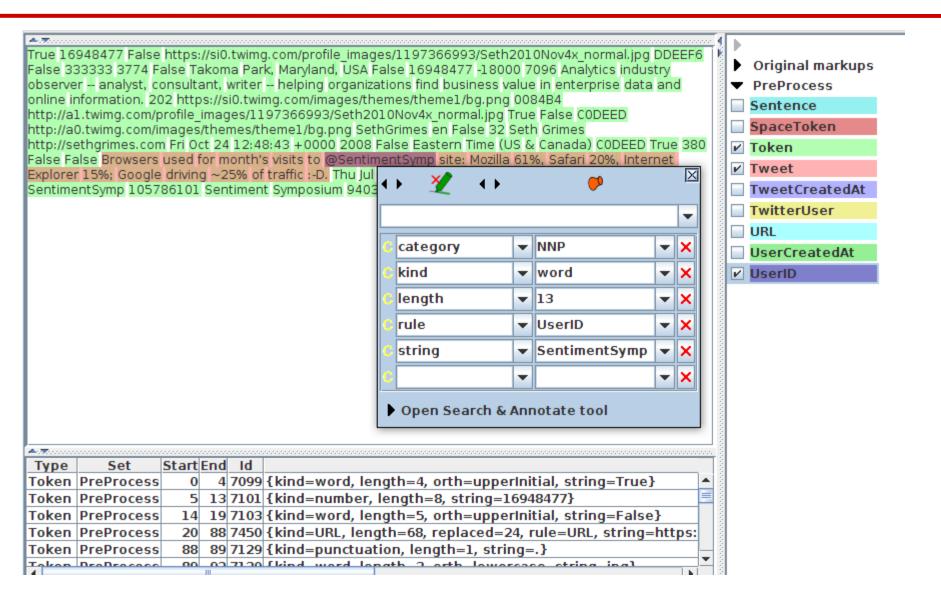


The GATE Twitter Tokeniser

- Treat RTs and URLs as 1 token each
- #nike is two tokens (# and nike) plus a separate annotation HashTag covering both. Same for @mentions
 -> UserID
- Capitalisation is preserved, but an orthography feature is added: all caps, lowercase, mixCase
- Date and phone number normalisation, lowercasing, and emoticons are optionally done later in separate modules
- Consequently, tokenisation is faster and more generic
- Also, more tailored to how ANNIE NER expects the input

GATE Twitter Tokeniser: An Example





Hands-on: Running GATE's Tweet Tokeniser

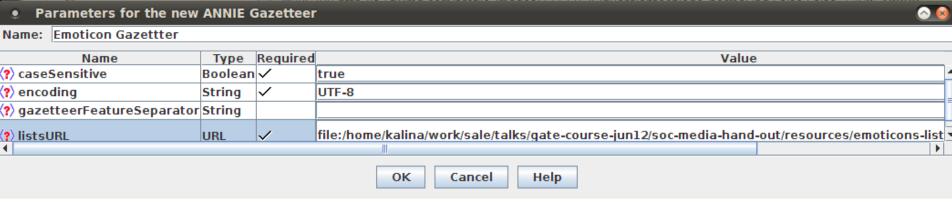


- Create a new application, call it Twitter App
- Load a Document Reset and Twitter Tokeniser
- Run app on your energy tweets and inspect results (Hashtag, UserID)
- This should give you roughly the same results
- Take a quick look at the actual rules for Hashtag and UserID recognition in tokeniser/twitter.jape. See how they differ from the simple ones we wrote earlier.

Emoticon Detection



- There is a gazetteer list of some commonly used emoticons in your handouts, resources/emoticons-list.
- Create an ANNIE Gazetteer PR, name it Emoticon gazetteer
- Change the default separator from : to \t (colons are often in smileys)
- Set the listsURL to the emoticons-lists.def file



Run the application

Inspect the Lookup annotations in GATE Developer



Tweet Normalisation

- "RT @Bthompson WRITEZ: @libbyabrego honored?!
 Everybody knows the libster is nice with it...lol...(thankkks a bunch;))"
- OMG! I'm so guilty!!! Sprained biibii's leg! ARGHHHHHH!!!!!!
- Similar to SMS normalisation
- For some components to work well (POS tagger, parser), it is necessary to produce a normalised version of each token
- BUT uppercasing, and letter and exclamation mark repetition often convey strong sentiment
- Therefore some choose not to normalise, while others keep both versions of the tokens

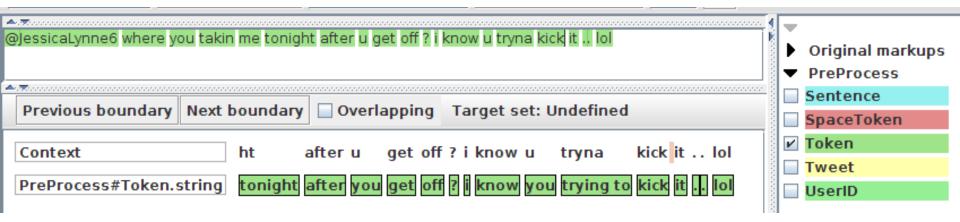


Lexical normalisation

- Two classes of word not in dictionary
 - 1. Mis-spelled dictionary words
 - 2. Correctly-spelled, unseen words (e.g. foreign surnames)
- Problem: Mis-spelled unseen words (these can be in the dict!)
- 1st challenge: separate out-of-vocabulary and in-vocabulary
- 2nd challenge: fix mis-spelled IV words
- Edit distance (e.g. Levenshtein): count character adds, removes
 - zseged → szeged (distance = 2)
 - Pronunciation distance (e.g. double metaphone):
 - YEEAAAHHH → yeah
- Need to set bounds on these, to avoid over-normalising OOV words

A normalised example





- Normaliser currently based on spelling correction and some lists of common abbreviations
- Outstanding issues:
 - Insert new Token annotations, so easier to POS tag, etc?
 For example: "trying to" now 1 annotation
 - Some abbreviations which span token boundaries (e.g. gr8, do n't) are not yet handled
 - Capitalisation and punctuation normalisation

GATE Tweet Normaliser



- Load the Tweet Normaliser PR
- Add it at the end of your pipeline
- Run the pipeline and inspect the results
- Check the features on **Token** annotations
- If you can't find any normalised words, just edit one of the tweets and add your own slang words to normalise!

Part-of-speech tagging: example



Many unknowns:

Music bands: Soulja Boy | TheDeAndreWay.com in stores Nov 2,

2010

Places: #LB #news: Silverado Park Pool Swim Lessons

Capitalisation issues:

@thewantedmusic on my tv:) aka derek

last day of sorting pope visit to <u>birmingham</u> stuff out

Don't Have Time To Stop In??? Then, Check Out Our Quick Full Service Drive Thru Window:)

Part-of-speech tagging: example



- Slang
- ~HAPPY <u>B-DAY</u> TAYLOR !!! <u>LUVZ YA</u>

- Orthographic errors
- dont even have <u>homwork</u> today, <u>suprising</u>?

Dialect

fancy a cheeky nandoz tho

Can I have a go on your iPad?

Part-of-speech tagging: issues



Unknown words fall roughly into two categories

Standard token, non-standard orthography;
 freinds
 KHAAAANNNNNN!



 Non-standard token, standard orthography omg + bieber → omb Huntingdon / Huntington



Load & configure the Stanford Tagger



- Load the StanfordCoreNLP plugin through the Plugin Manager
- Create an instance of Stanford POS Tagger with this model: resources/gate-EN-twitter.model
- Add to the end of the application and run it

Let's compare ANNIE and TwitIE

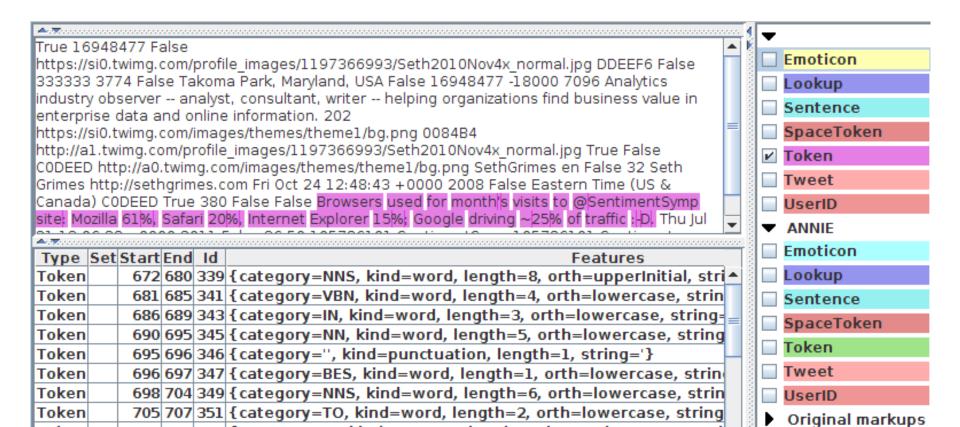


- Load the ANNIE application
- Change the annotationSetName, inputAS and outputAS parameters to ANNIE for every PR
- Run it
- Now, carefully, go to your TwitIE application and set the Document Reset parameters to keep the ANNIE annotation set (setsToKeep – add ANNE to the list)
- Otherwise, it would get removed when we run TwitIE
- Now run TwitlE again

TwitIE POS Tagger Results: Example



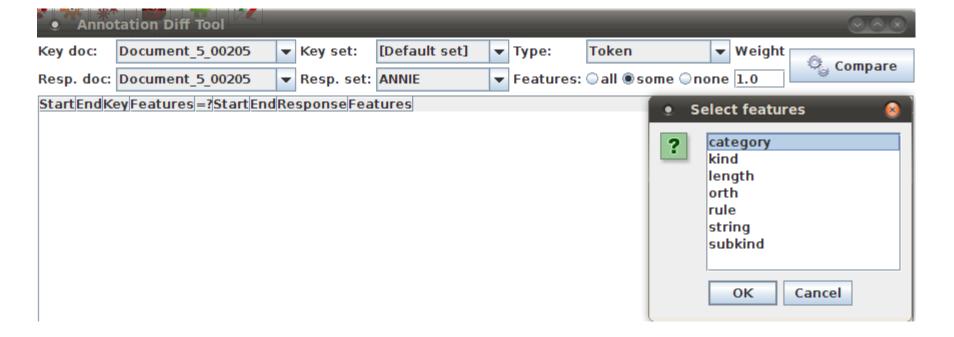
- You should get results in 2 sets:
 - ANNIE will have the POS tags from the ANNIE POS Tagger
 - The default set will have those from the TwitlE Tagger



Compare Differences: Annotation Diff



- Click on the Annotation Diff button
- 1
- Select a document from the test corpus (same Key and Resp)
- Key set: [Default set]; Resp. set: ANNIE
- Type: Token; Features: some, then select: category



Compare Differences (2)



- Click on the Compare button
- Inspect the results; repeat for 1-2 more documents
- HINT: Clicking on the Start column will sort tokens by offset

Start	End	Key	Features	=?	Start	End Response	Features
736	741	Nokia	{category=NNP, kind=gth=5, string=Nokia}	=	736	741 Nokia	{category=NNP, kind=gth=5, string=Nokia}
742	747	Posts	{category=VBZ, kind=gth=5, string=Posts}	=	742	747 Posts	{category=VBZ, kind=gth=5, string=Posts}
748	752	Huge	{category=JJ, kind=wngth=4, string=Huge}	=	748	752 Huge	{category=JJ, kind=wngth=4, string=Huge}
753	762	Quarterly	{category=JJ, kind=w9, string=Quarterly}	=	753	762 Quarterly	{category=JJ, kind=w9, string=Quarterly}
763	767	Loss	{category=NN, kind=wngth=4, string=Loss}	=	763	767 Loss	{category=NN, kind=wngth=4, string=Loss}
767	768	,	{string=,, length=1,tuation, category=,}	=	767	768,	{string=,, length=1,tuation, category=,}
769	773	Sees	{category=VBZ, kind=ngth=4, string=Sees}	<>	769	773 Sees	{category=NNP, kind=ngth=4, string=Sees}
774	780	Better	{category=NNP, kind=th=6, string=Better}	=	774	780 Better	{category=NNP, kind=th=6, string=Better}
781	786	Times	{category=NNP, kind=gth=5, string=Times}	=	781	786 Times	{category=NNP, kind=gth=5, string=Times}
787	792	Ahead	{category=NNP, kind=gth=5, string=Ahead}	=	787	792 Ahead	{category=NNP, kind=gth=5, string=Ahead}
793	794	-	{category=:, subkind length=1, string=-}	=	793	794 -	{category=:, subkind length=1, string=-}
795	819	http://on	{rule=URL, temp_cateed=13, category=URL}	<>	795	819 http://o	{rule=URL, temp_cateced=13, category=CD}

 We are still improving the tweet POS model, but major improvements make it current state-of-the-art