GATE and Social Media: Language ID, tokenisation and hashtags

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NLP Pipelines

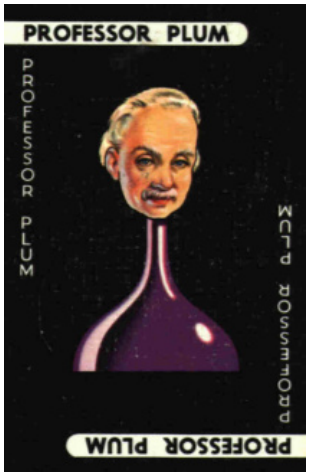
Text

Language ID

Tokenisation

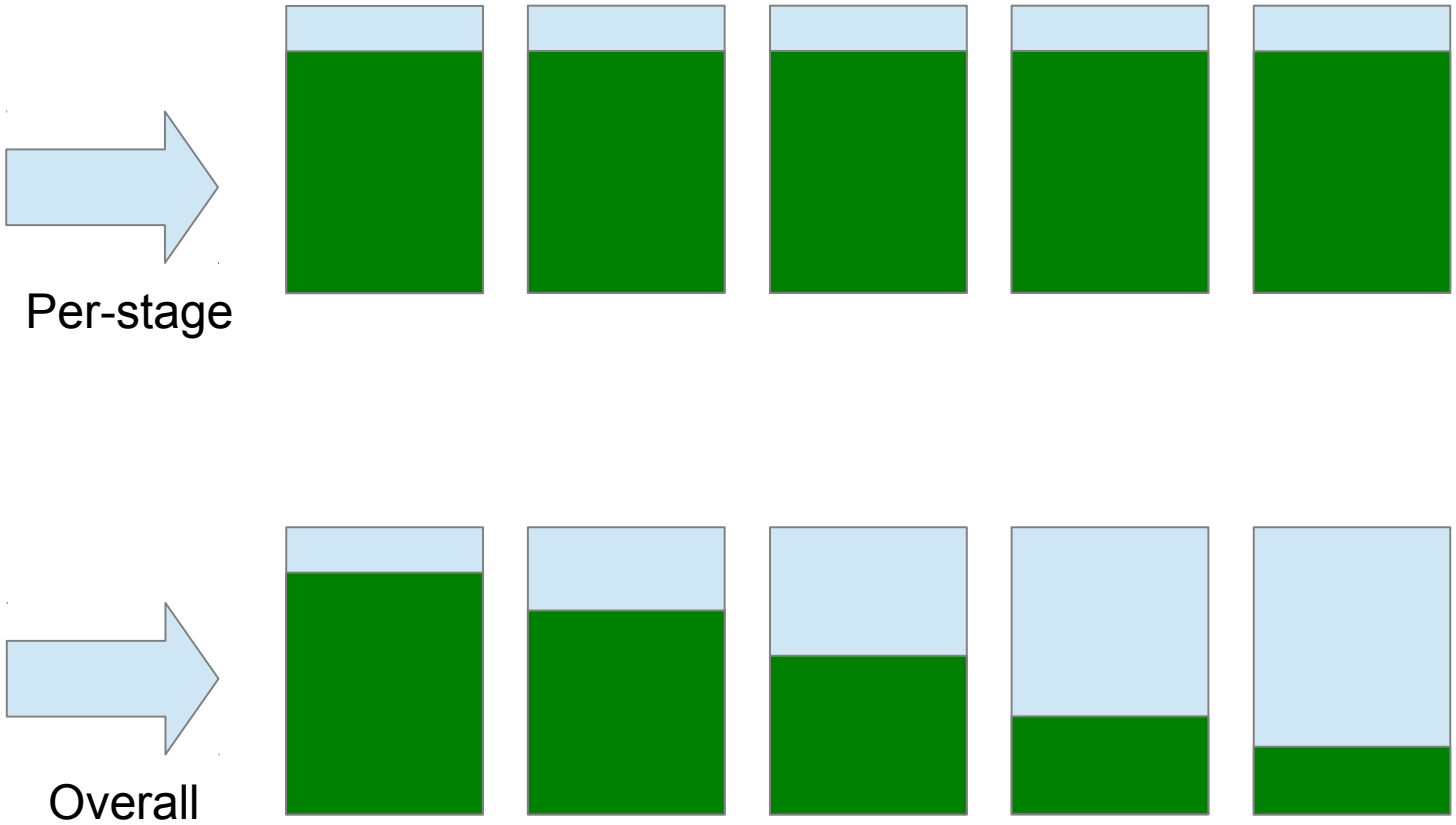
Part of speech tagging

Typical annotation pipeline



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 intended to be.

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(:

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

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

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

Language ID: issues

General accuracy on microblogs: 89.5% (Preotiuc-Pietro 2012)
Compared to accuracy on formal text: 99.4% (Carter 2013)

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

- 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 sources of 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.

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

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

The variety of data and sparsity of features makes selection important

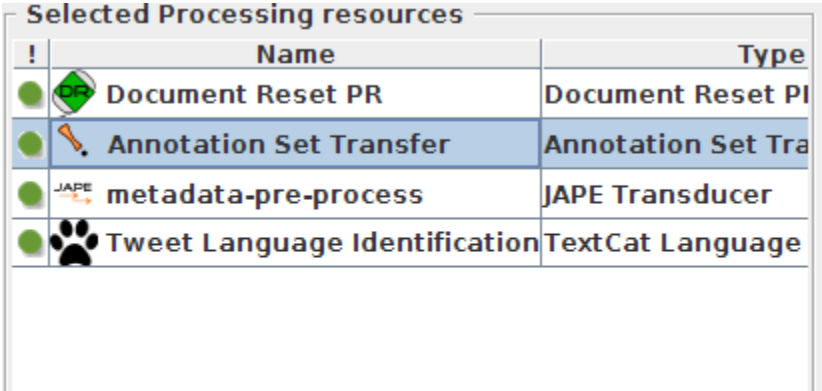
- LD focuses on task-relevant features using information gain
- Features with a high LD score are informative about language, without being informative about domain
- Candidate features pruned before applying LD based on term frequency

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

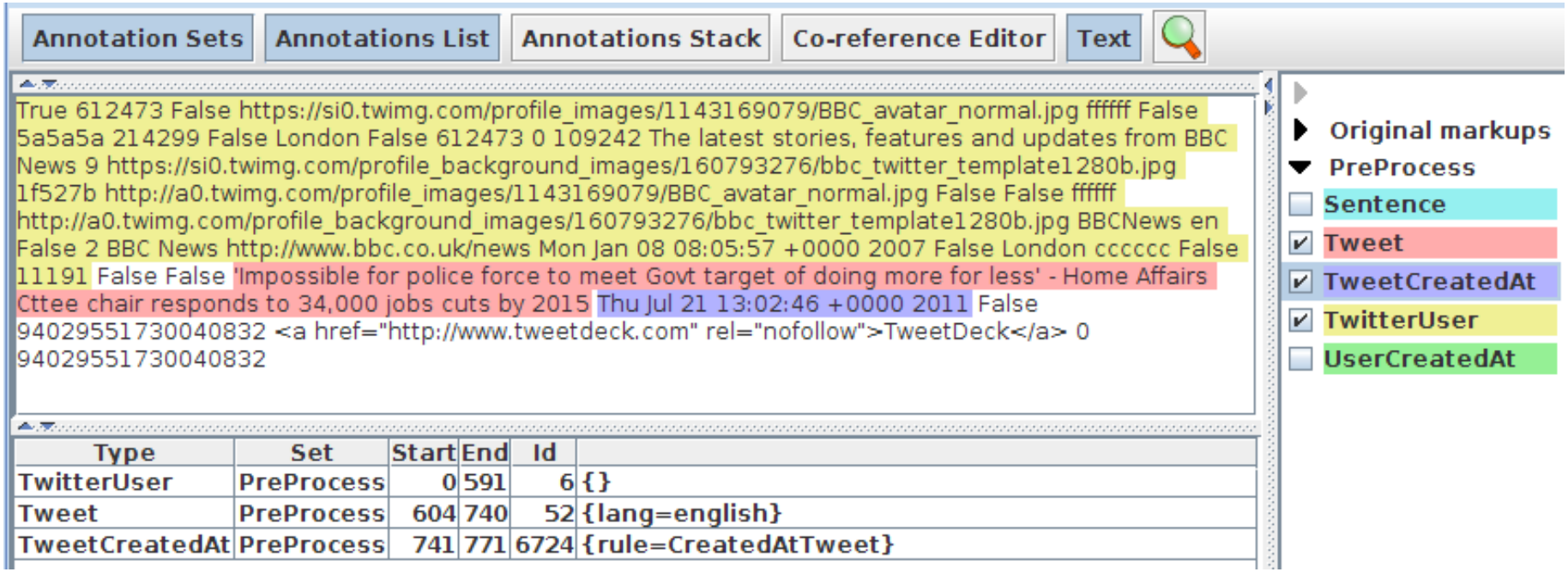
- Consistent improvement over plain TextCat, LangDetect and CLD
- Limited to no training data available for the 97 target languages

Hands-On 1: Language ID

- Load **twitie-lang-id.xgapp** in GATE (Restore Application From File)
- Create a new corpus, save to DS and load **lang-id-small-test-set.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
- 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 asssneezes 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 → does n't
- doesnt → doesnt
- Introduces previously-unseen tokens

Smileys and emoticons

- I <3 you → I & lt ; you
- This piece ;,,(so emotional → This piece ; , , (so emotional
- Loss of information (sentiment)

Punctuation for emphasis

- *HUGS YOU**KISSES YOU* → * HUGS YOU**KISSES YOU *

Words run together / skip

- I wonde rif Tsubasa is okay..

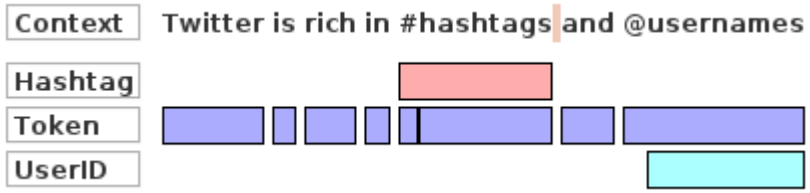
Tokenisation: solutions

O'Connor et al. (2010) apply a regular expression tokeniser to tweets, with the following adaptations:

- Treat #hashtags, @mentions, abbreviations, strings of punctuation, emoticons and UTF glyphs as single tokens
- Made available as “twokenizer” tool

Bontcheva et al. (2013) 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 → # open access
  - #swankkkkk → # swan kkk k k ?

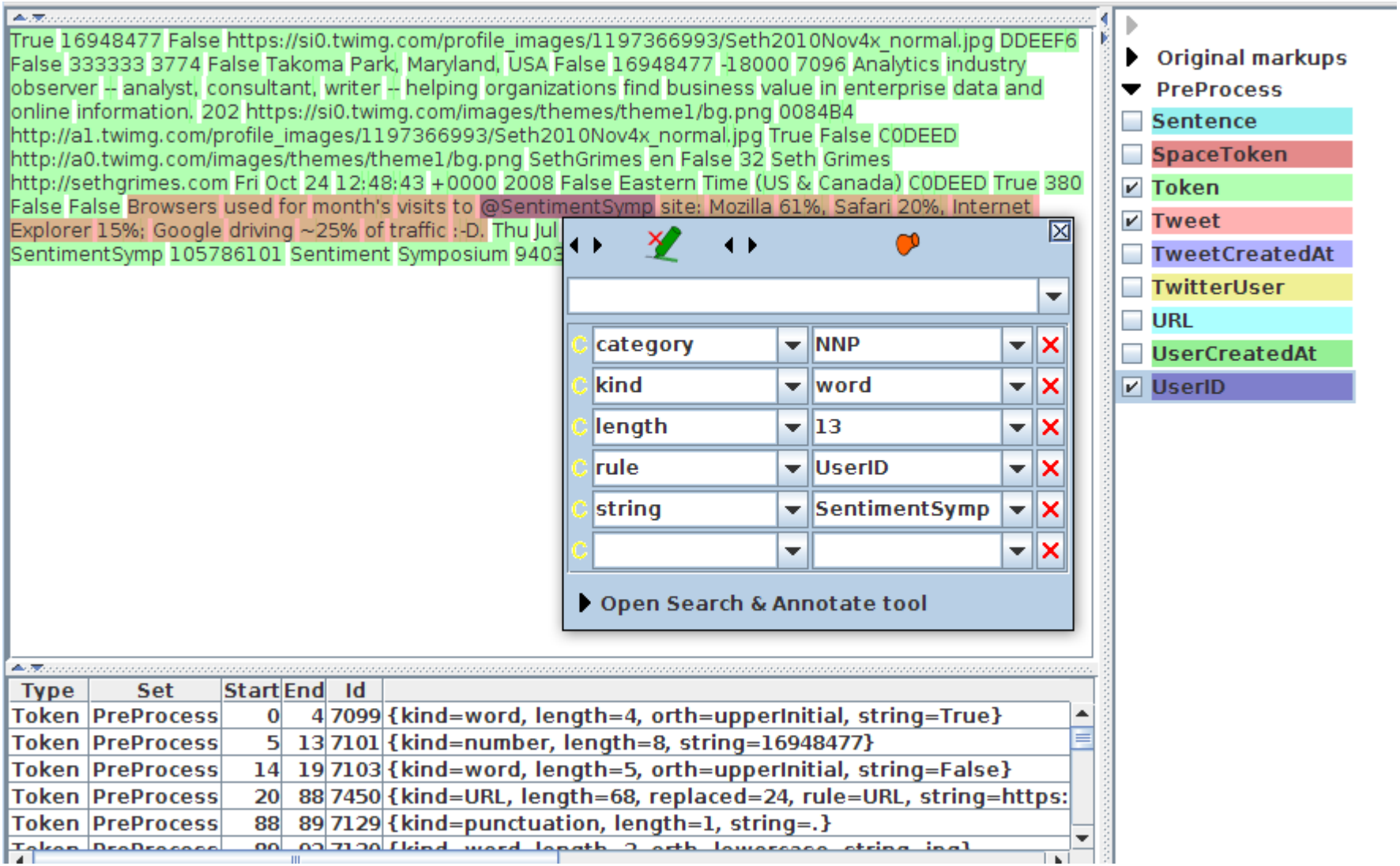
Hands-On: Hashtag and @mention tokenisation

- Load the **GATE Unicode Tokeniser** PR, with its default settings
- Load a **Document Reset** PR with defaults
- Create a new corpus pipeline app; add Reset, then the Tokeniser
- Create a new corpus and populate from single concatenated file, using **test-10-tweets.xml** (Root element: **doc_root**)
- Inspect the results, especially around hashtags and @mentions
- It helps to show the “text” annotation from the “Key” AS
- 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
- Right-click on the JAPE transducer, re-load, and re-run the app

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

- Right click on Processing Resources, load ANNIE English Tokeniser
  - Leave TokeniserRulesURL unchanged
  - For **TransducerGrammarURL** navigate to your hands-out directory, then choose **resources/tokeniser/twitter.jape**
- Add this Tweet Tokeniser at the end of the **TwitIE tutorial app**
- Set the AnnotationSetName parameter to **PreProcess**
- Run app on the 10 tweets and inspect results (Hashtag, UserID)
- Note that the Token annotations under UserIDs have now PoS category NNP, since they are proper names
- Take a quick look at the actual rules for Hashtag and UserID recognition in twitter.jape. See how they differ from the simple ones we wrote earlier.