Machine Learning

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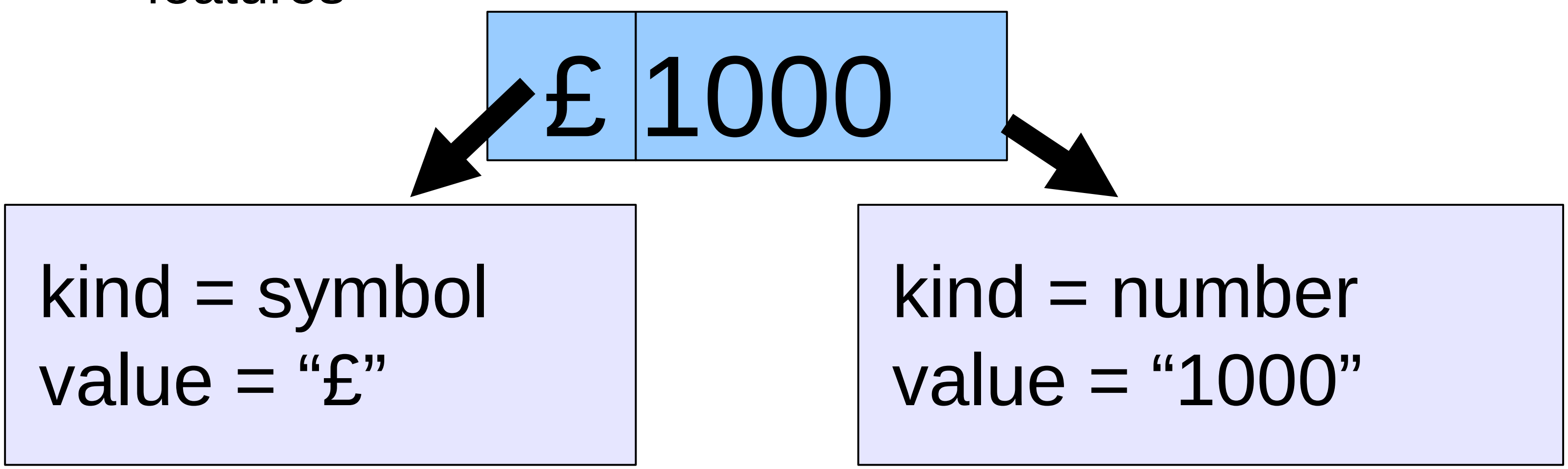
Overview of the day

- Practical introduction to ML in GATE in the context of an entity recognition task (finding mentions in text, such as drug names)
  - Using the **Batch Learning PR**
  - How to train, apply and evaluate a machine learning model over GATE data
- Some theory and background about machine learning for natural language processing
- Practical session on text classification using the **Learning Framework PR**

Why Machine Learning?

- Automating the process of inferring new data from existing data
- In GATE, that means creating annotations by learning how they relate to other annotations
- For example, we have "Token" annotations with "kind" and "value" features



- ML could learn that a "£" followed by a number is an amount of currency

How is that better than making rules?

- It is different to the rule-based approach
- Humans are better at writing rules for some things, and ML algorithms are better at finding some things
- With ML you don't have to create all the rules
- However, you have to manually annotate a training corpus (or get someone else to do it!)
- Rule-based approaches (e.g. JAPE) and ML work well together; JAPE is often used extensively to prepare data for ML

Terminology: Instances, attributes, classes

California Governor Arnold Schwarzenegger proposes deep cuts.

Instances: Any annotation
Tokens are often convenient

Token | Token | Token | Token | Token | Tok | Tok

Attributes: Any annotation feature relative to instances
Token.String
Token.category (POS)
Sentence.length

Sentence

Class: The thing we want to learn
A feature on an annotation

Entity.type =Location | Entity.type=Person

Instances

- Instances are cases that may be learned
- Every instance is a decision for the ML algorithm to make
- To which class does this instance belong?
  - “California” → Location

GATE

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Attributes: Any annotation feature relative to instances

Token.String

Token.category (POS)

Sentence.length

Sentence

Class: The thing we want to learn

A feature on an annotation

Entity.type =Location

Entity.type=Person

Attributes

- Attributes are pieces of information about instances
- They are sometimes called “features” in machine learning literature
- Examples
  - Token.string == “Arnold”
  - Token.orth == upperInitial
  - Token(-1).string == “Governor”

Terminology: Instances, attributes, classes

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Attributes: Any annotation feature relative to instances
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Token.category (POS)
Sentence.length

Sentence

Class: The thing we want to learn
A feature on an annotation

Entity.type =Location

Entity.type=Person

Classes

- The class is what we want to learn
- Suppose we want to find persons' names: for every instance, the question is “is this a person name?” and the classes are “yes” and “no”
- Sometimes there are many classes, for example we may want to learn entity types
  - For every instance, the question is “which type from the list does this instance belong to?”
  - One answer is “none of them”

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Token.String
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Sentence.length

Sentence

Class: The thing we want to learn
A feature on an annotation

Entity.type =Location

Entity.type=Person

Machine Learning in GATE

- GATE supports machine learning in several ways
- Some of the **standard PRs** are ML-based e.g.
  - ANNIE POS tagger
  - Stanford parser
- **Machine Learning PR**
  - Provides Weka integration, but is a little out of date and only supports token-based attributes – though you can get around this using JAPE
- **Third-party NLP components**
  - e.g. the OpenNLP PR can be used with any models, trained externally to GATE
- **Roll-your-own**
  - It is relatively straightforward to write a PR that will create learning instances from your text, and export them in a format suitable for your favourite ML toolkit. Or even to integrate more fully.

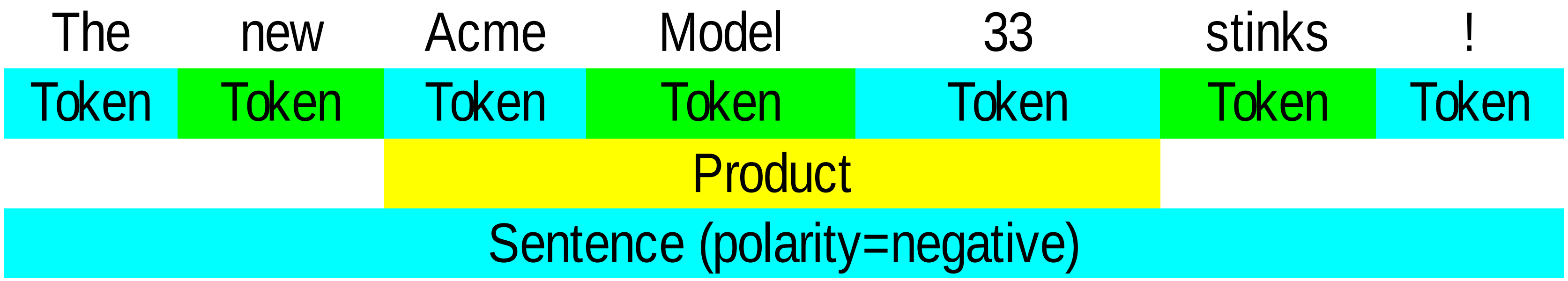
Batch Learning PR

- We will not look at any of the above in this tutorial
- We will be looking at the **Batch Learning PR** initially, then the **Learning Framework PR** later in the day
- Advantages to the Batch Learning PR
  - Simple to use and configure
  - Good annotation to attribute mapping
  - Hides the mapping of NLP tasks to multiple binary classification problems
  - Provides its own evaluation framework
  - Support for common ML algorithms (SVM, Perceptron, some Weka algorithms)
  - Supports combined NER and classification in an easy and successful (published) way
- Disadvantages
  - Heavily biased to SVM
  - Inflexible: hard to dig in to the code
  - Hard to extend to more recent algorithms

ML Tasks in the Batch Learning PR

- The Batch Learning PR supports 3 types of ML tasks:
- chunk recognition (named entity recognition, NP chunking) as in the previous example
- text classification (sentiment classification, POS tagging) as in the following example
- relation annotation (this requires special techniques that are not covered in this module, although materials are available)

Example: text classification



- instance: Sentence annotation
- attributes: Token and Product annotations and their features (suppose that the Product annotations have been created earlier with gazetteers and rules)
- class: polarity= “negative”

- ML could learn that a Product close to the Token “stinks” expresses a negative sentiment, then add a polarity=“negative” feature to the Sentence.

Training

- Training involves presenting data to the ML algorithm from which it creates a model
- The training data (instances) have been annotated with class annotations as well as attributes
- Models are representations of decision-making processes that allow the machine learner to decide what class the instance has based on the attributes of the instance

Application

- When the machine learner is applied, it creates new class annotations on data using the model
- The corpus it is applied to must contain the required attribute annotations
- The machine learner will work best if the application data is similar to the training data

Evaluation

- We want to know how good our machine learner is before we use it for a real task
- Therefore we apply it to some data for which we already have class annotations
  - The “right answers”, sometimes called “gold standard”
- If the machine learner creates the same annotations as the gold standard, then we know it is performing well
- The test corpus must not be the same corpus as you trained on
  - This would give the machine learner an advantage, and would give a false idea of how good it is
- GATE's ML PR has a built-in evaluation mode that splits the corpus into training and test sets and cross-validates them

Setting up a Corpus

Load the corpus

- Create a corpus (any name is fine; you can even leave it blank)
- Populate it from ner/corpus/*.xml in the hands-on materials
  - Set the encoding to UTF-8
- You should get 93 documents (numbered 0 to 92 in the corpus)
- Open a document and examine its annotations

Examining the corpus

- The corpus contains an annotation set called “Key”, which has been manually prepared
- Within this annotation set are annotations of types “Date”, “Location”, “Money”, “Organization” and so forth
- There are also some annotations in the “Original markups” set (these represent HTML tags)

What are we going to do with this corpus?

- We are going to train a machine learner to annotate corpora with these entity types
- We need a training corpus and a test corpus
- The training corpus will be used by the machine learner to deduce relationships between attributes and entity types (classes)
- The test corpus will be used to find out how well it is working, by comparing annotations created by the learner with the correct annotations that are already there
- In *Evaluation* mode, which we will try first, the ML PR automatically splits one corpus up into training and test sets

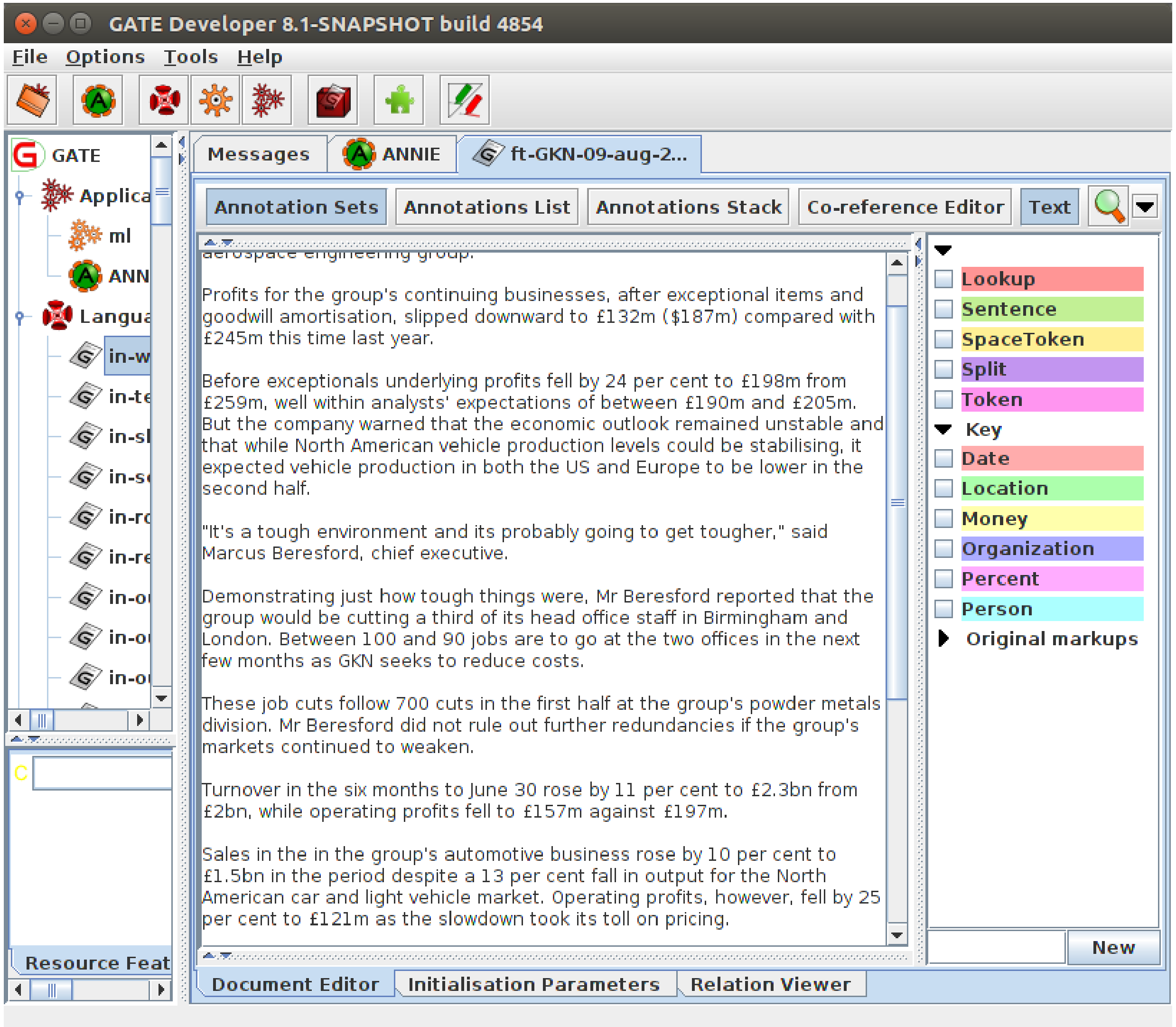
Instances and Attributes

- This corpus so far contains only the class annotations
- There is not much in this corpus to learn from
- What would our instances be?
- What would our attributes be?
- If we run parts of ANNIE over the corpus, then we can use:
  - Token annotations for instances
  - Token features for attributes
  - Gazetteer Lookups for attributes

Instances and Attributes

- Load ANNIE
- We only want
  - Tokens and some basic features
  - Gazetteer Lookups
- So remove the last two Prs from the pipeline
  - ANNIE NE Transducer
  - ANNE Orthomatcher
- Check that the document reset PR's setsToKeep parameter includes “Key”!
- Run this cut-down ANNIE over your corpus

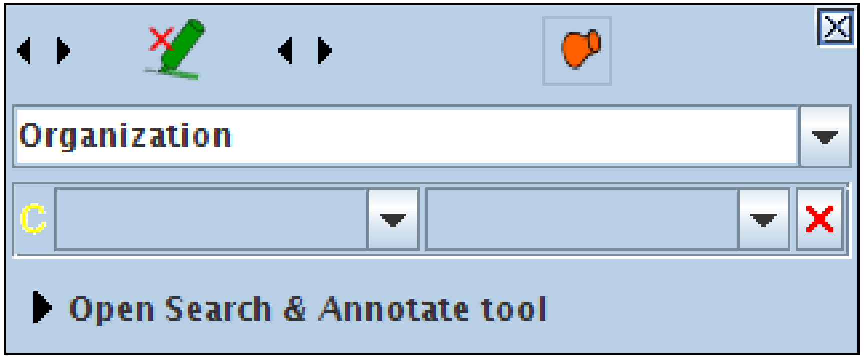
Running ANNIE on the corpus



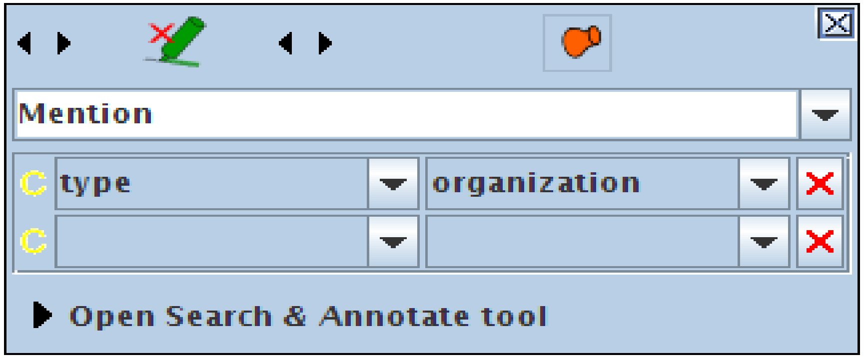
- Having run ANNIE on the corpus, we have more annotations to work with

Preparing the corpus: Classes

- What we have:



- What we need:



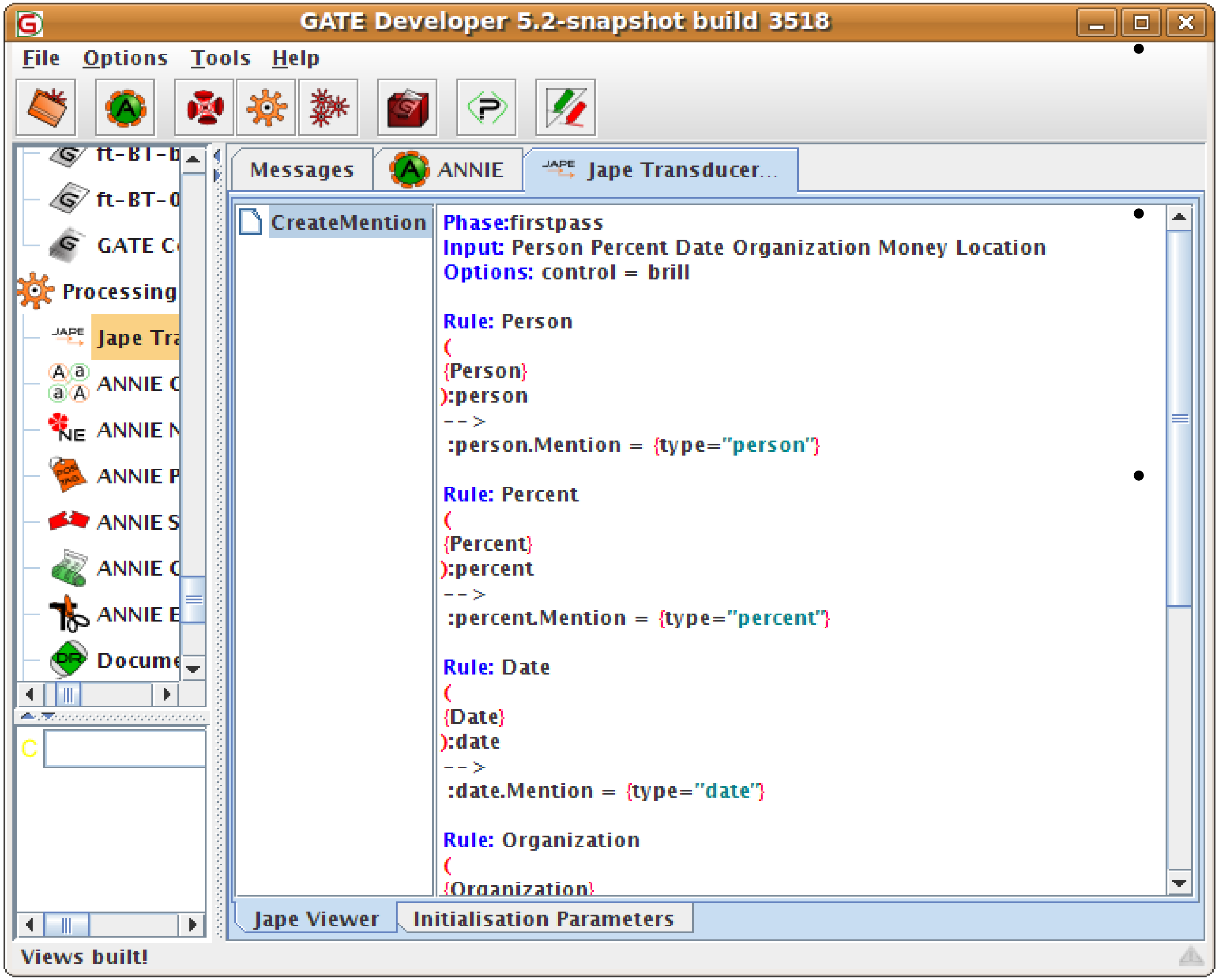
Preparing the corpus: Classes

- Currently each class has its own annotation type (Date, Person, Percent etc.)
- But the ML PR expects the class (ML term) to be a feature value, not an annotation type
- So we need to make a new annotation type for the ML to learn from: “Mention” (it doesn't matter what it's called as long as we're consistent and configure the PR to match)

Making class annotations

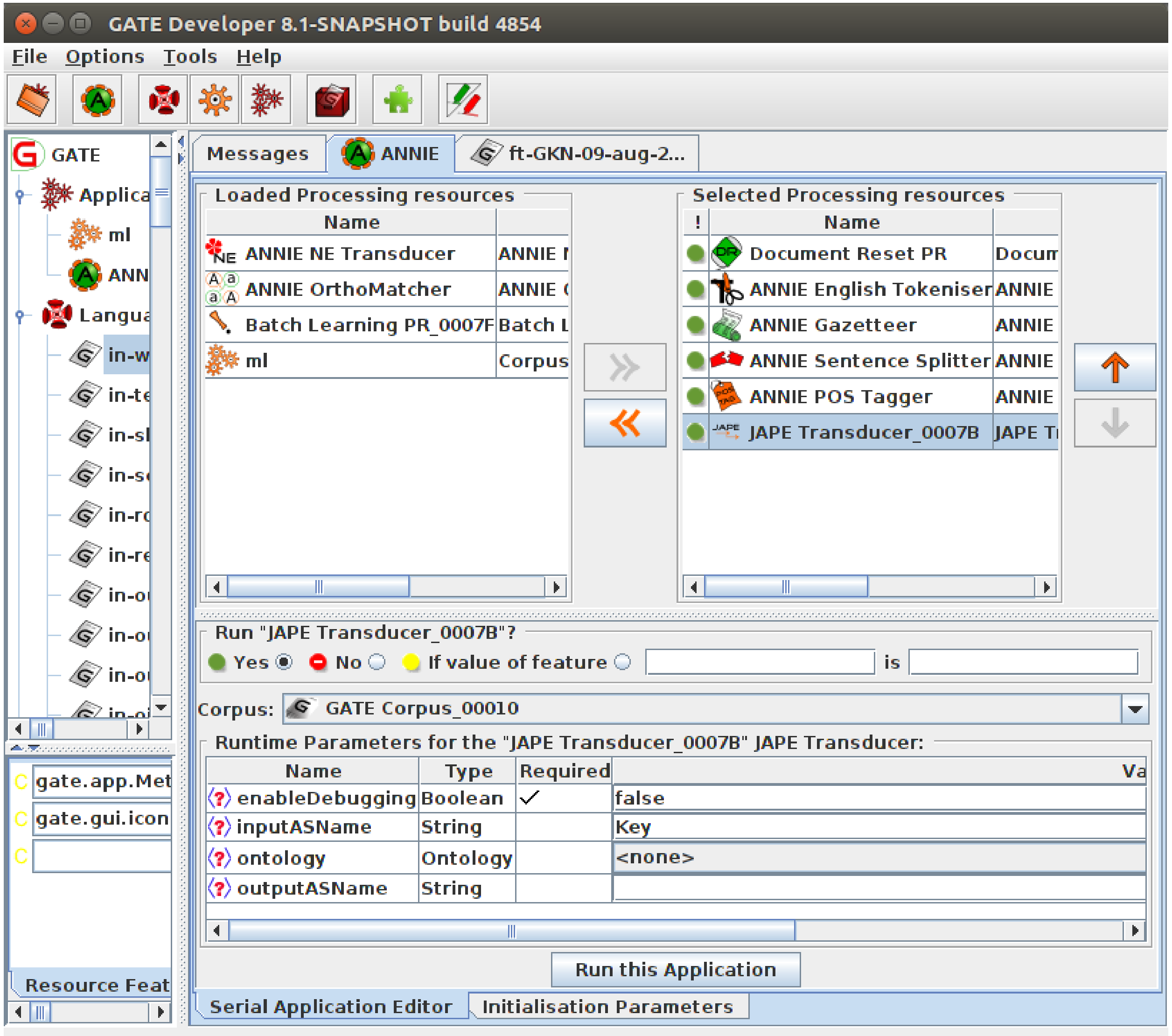
- **Load a JAPE transducer from the ner/CreateMention.jape grammar**
- **Look at the grammar in GATE**

The CreateMention.jape grammar



- This grammar makes a new annotation type called "Mention"
- It makes the previous annotation type into a feature of the "Mention" annotation
- Feature name is "type" because "class" is reserved for ontology use

Applying the grammar to the corpus

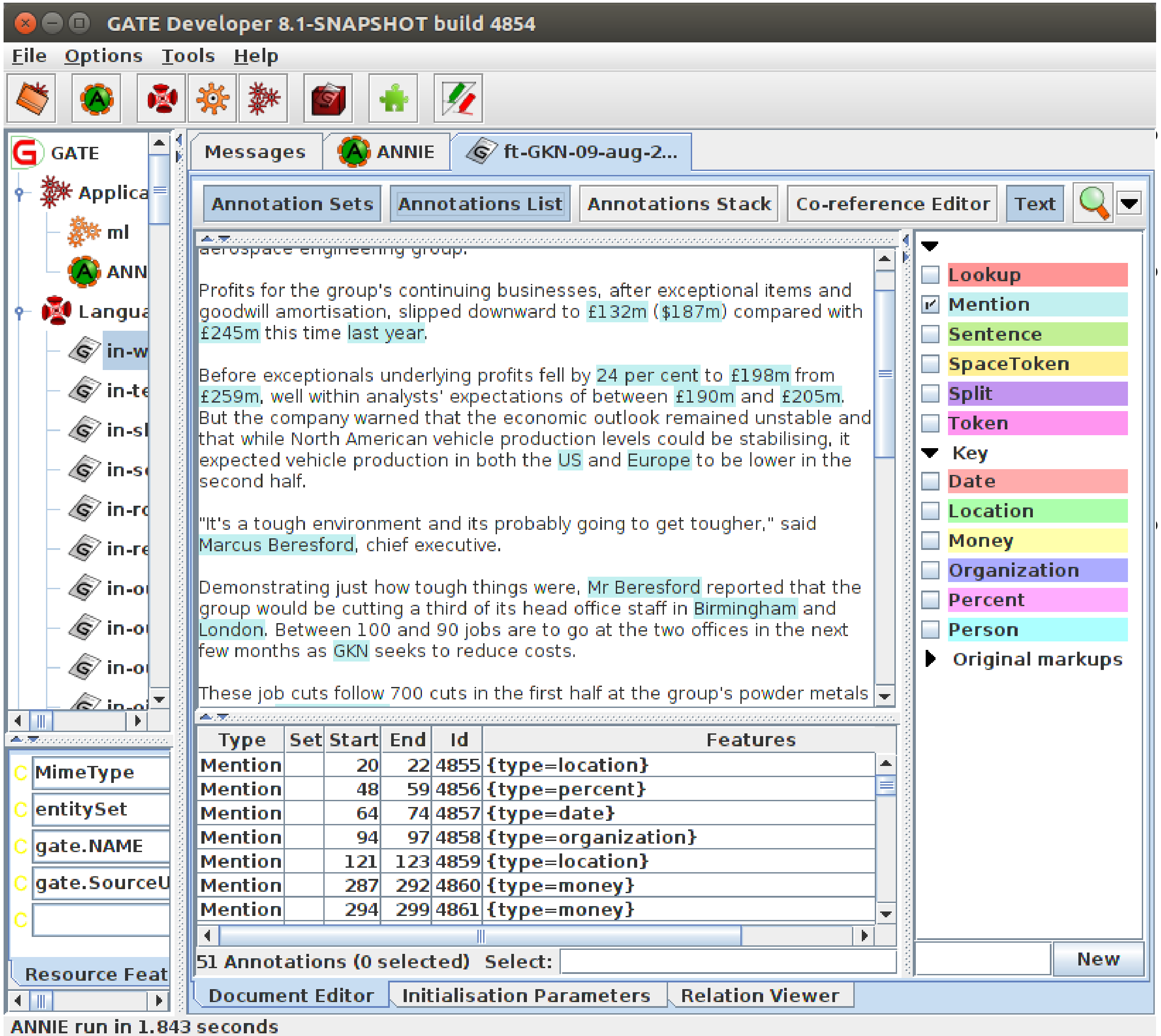


Add the JAPE transducer at the end of your application

Set the inputASName to "Key"

Leave the outputASName blank (default)

Check the “Mention” annotations



Rerun the application

Check that you have some “Mention” annotations

Check that they have a feature “type” and that the values look right

Check the “Mention” annotations

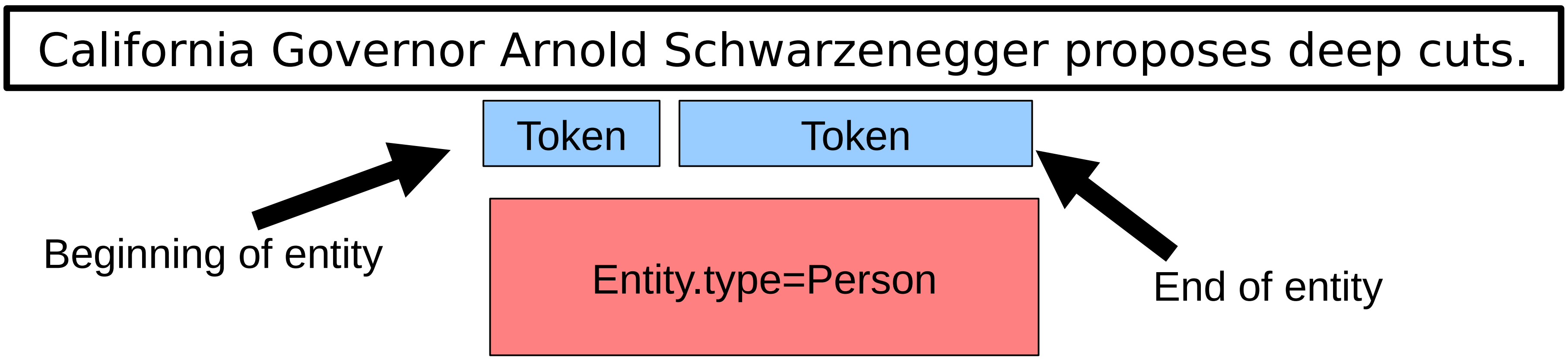
- **Check that you have some “Mention” annotations**
- **Check that they have a feature “type” and that the values look right**
- **These Mention annotations are derived from the named entities in the “Key” AS, and will form our instances**

The Configuration File

Looking at the configuration file

- In the configuration file, we tell the machine learning PR what we want it to do
- You will find a configuration file in your hands-on materials, called ner/ner-config-file.xml
- **Open it using a text editor**

<SURROUND value="true"/>



- The class to be learned covers more than one instance (chunking problem)
- The PR has to learn the boundaries (chunking problem)
- So we tell the PR to use ***surround mode***

Confidence Thresholds

```
<PARAMETER name="thresholdProbabilityEntity" value="0.2"/>
<PARAMETER name="thresholdProbabilityBoundary" value="0.4"/>
```

- Classifiers provide confidence ratings—how likely a result is to be correct
- We must determine how certain is good enough
- Depending on the application we might prefer to include or exclude annotations for which the learner is not too sure
- thresholdProbabilityBoundary is a threshold for the beginning and end instances
- thresholdProbabilityEntity is a threshold for beginning and end instances combined

<multiClassification2Binary method="one-vs-others"/>

California Governor Arnold Schwarzenegger proposes deep cuts.

Entity.type =Location

Entity.type=Person

- Many algorithms are binary classifiers (e.g. yes/no)
- We have several classes (Person, Location, Organization etc.)
- Therefore the problem must be converted to a set of binary problems, so we can use binary algorithms
- **one-vs-others**
  - LOC vs PERS+ORG / PERS vs LOC+ORG / ORG vs LOC+PERS
- **one-vs-another**
  - LOC vs PERS / LOC vs ORG / PERS vs ORG

<multiClassification2Binary method="one-vs-others"/>

- With more than 3 classes, **one-vs-another** becomes very computationally expensive!
- **one-vs-others**: N classes => N classifiers
  - A vs B+C+D, B vs A+C+D, C vs A+B+D, D vs A+B+C
- **one-vs-another**: N classes => N×(N-1)/2 classifiers
  - A vs B, A vs C, A vs D, B vs C, B vs D, C vs D

<EVALUATION method="holdout" ratio="0.66"/>

- We are going to evaluate our application in two ways today
  - The ML PR can automatically evaluate for us
  - We will also run our own evaluation
- This parameter dictates how the ML PR will work in evaluation mode
- The PR ignores this part of the config file in training and application modes

Evaluation

<EVALUATION method="kfold" runs="4"/>

OR

<EVALUATION method="holdout" ratio="0.66"/>

- Holdout randomly picks *ratio* documents for training and uses the rest for testing; this is faster than k-fold because it only runs once
- k-fold cross-validation will give you more reliable results and lets you “stretch” your corpus

K-Fold Cross-Validation

- In k-fold cross-validation, the corpus is split into k equal parts, and the learner is trained k times on k-1 parts and evaluated on 1; the results are averaged
- For example, if k=4, the documents are split into groups A, B, C, & D, then:
  - train on A+B+C, test on D;
  - train on A+B+D, test on C;
  - train on A+C+D, test on B;
  - train on B+C+D, test on A;
  - average these 4 results
- This maximises the use of the training data without losing testing accuracy, but takes 4 times as long

<ENGINE nickname="SVM" ..

- Next we specify what machine learning algorithm we wish to use
- Today we are using the SVM (“SVM”)
- We will use the following options: options="-t 0 -m 100 -tau 0.4"
  - Challenge: find out what these options do! (Hint: user guide §19.2)

<INSTANCE-TYPE>...

- Next, we tell the ML PR what our instance annotation is
- **The goal of the ML PR is to try to learn how the attributes of every instance predict its class**, so the instance is an important choice
- We have decided that the “Token” is our instance annotation type
  - We have run the tokenizer to ensure we have Token annotations in our corpus
  - The POS tagger adds category features to the Token annotations

Specifying Attributes

```
<ATTRIBUTELIST>
  <NAME>POS</NAME>
  <SEMTYPE>NOMINAL</SEMTYPE>
  <TYPE>Token</TYPE>
  <FEATURE>category</FEATURE>
  <RANGE from="-2" to="2"/>
</ATTRIBUTELIST>
```

- For every attribute, we create a specification like the one above
- This is the information from which the PR will learn, so it is important to give it some good data
- You can see in the configuration file that there are several attributes (including Lookup.majorType), providing a good range of information
- However, if you have too many attributes it can take a very long time to learn!

Breaking down the attribute specification

- <NAME>POS</NAME>
  - This is the name that we choose for this attribute. It can be anything we want, but it will help us later if we make it something sensible!
- <SEMTYPE>NOMINAL</SEMTYPE>
  - Is the value of this attribute a number or a name?

Breaking down the attribute specification

- <TYPE>Token</TYPE>
  - The value of the attribute will be taken from the "Token" annotation
- <FEATURE>category</FEATURE>
  - The value of the attribute will be taken from the "category" feature

Breaking down the attribute specification

```
<ATTRIBUTELIST>
  :
  <RANGE from="-2" to="2"/>
</ATTRIBUTELIST>
```

- Because this is an “ATTRIBUTELIST” specification, we can specify a “RANGE”
- In this case, we will gather attributes from the current instance and also the preceding and following two; i.e., a window of 5 Token annotations centred on the one in question

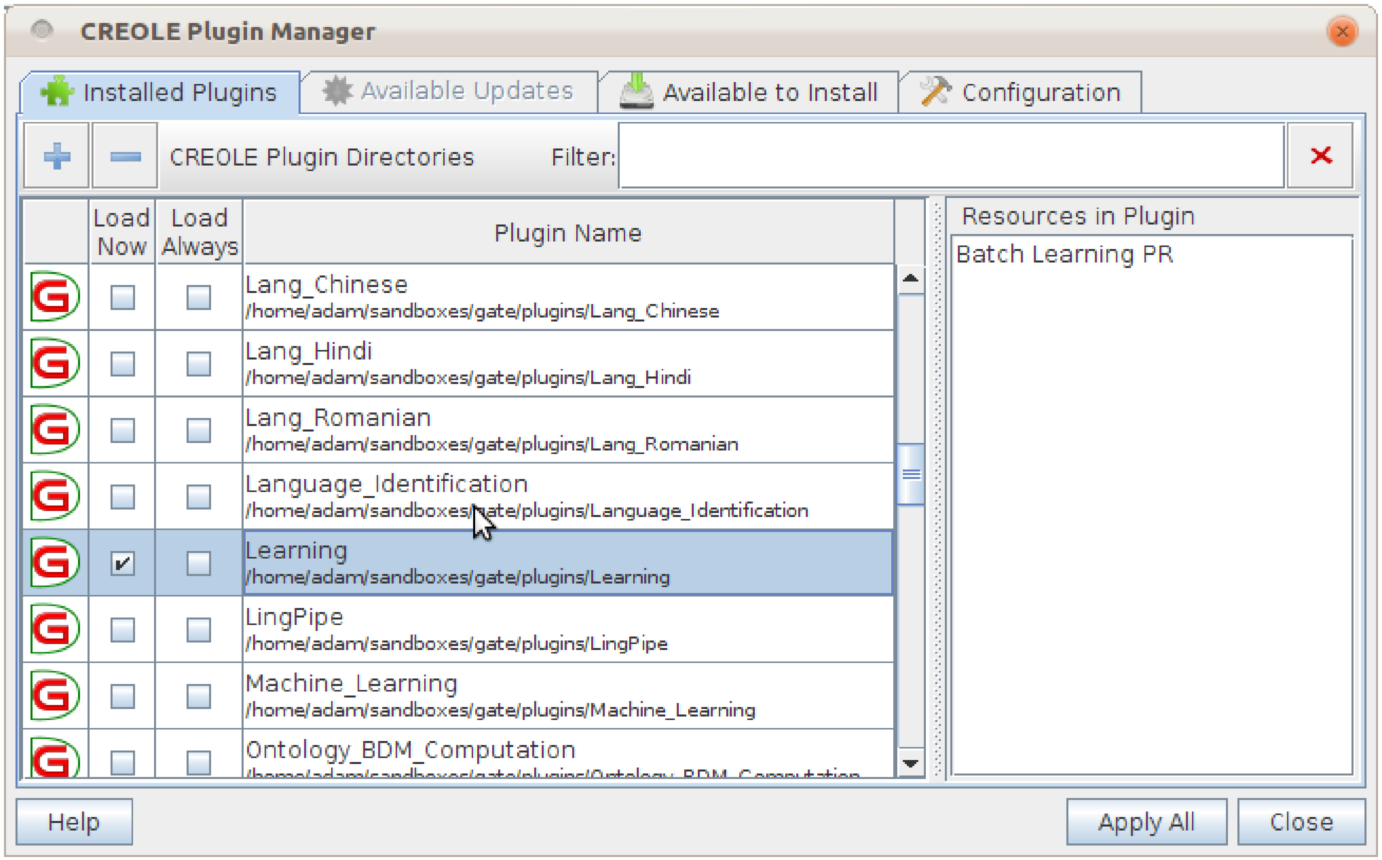
Specifying the Class Attribute

```
<ATTRIBUTE>
    <NAME>Class</NAME>
    <SEMTYPE>NOMINAL</SEMTYPE>
    <TYPE>Mention</TYPE>
    <FEATURE>type</FEATURE>
    <POSITION>0</POSITION>
    <CLASS/>
</ATTRIBUTE>
```

- You can call the class attribute whatever you want, but “Class” is a sensible choice
- Remember that our class attribute is the “type” feature of the “Mention” annotation
- This is an ATTRIBUTE, not an ATTRIBUTELIST, so we have “position”, not “range”
- The <CLASS/> element tells the Batch Learning PR that this is the class attribute to learn.

Running the ML PR in evaluation mode

Loading the Learning plugin

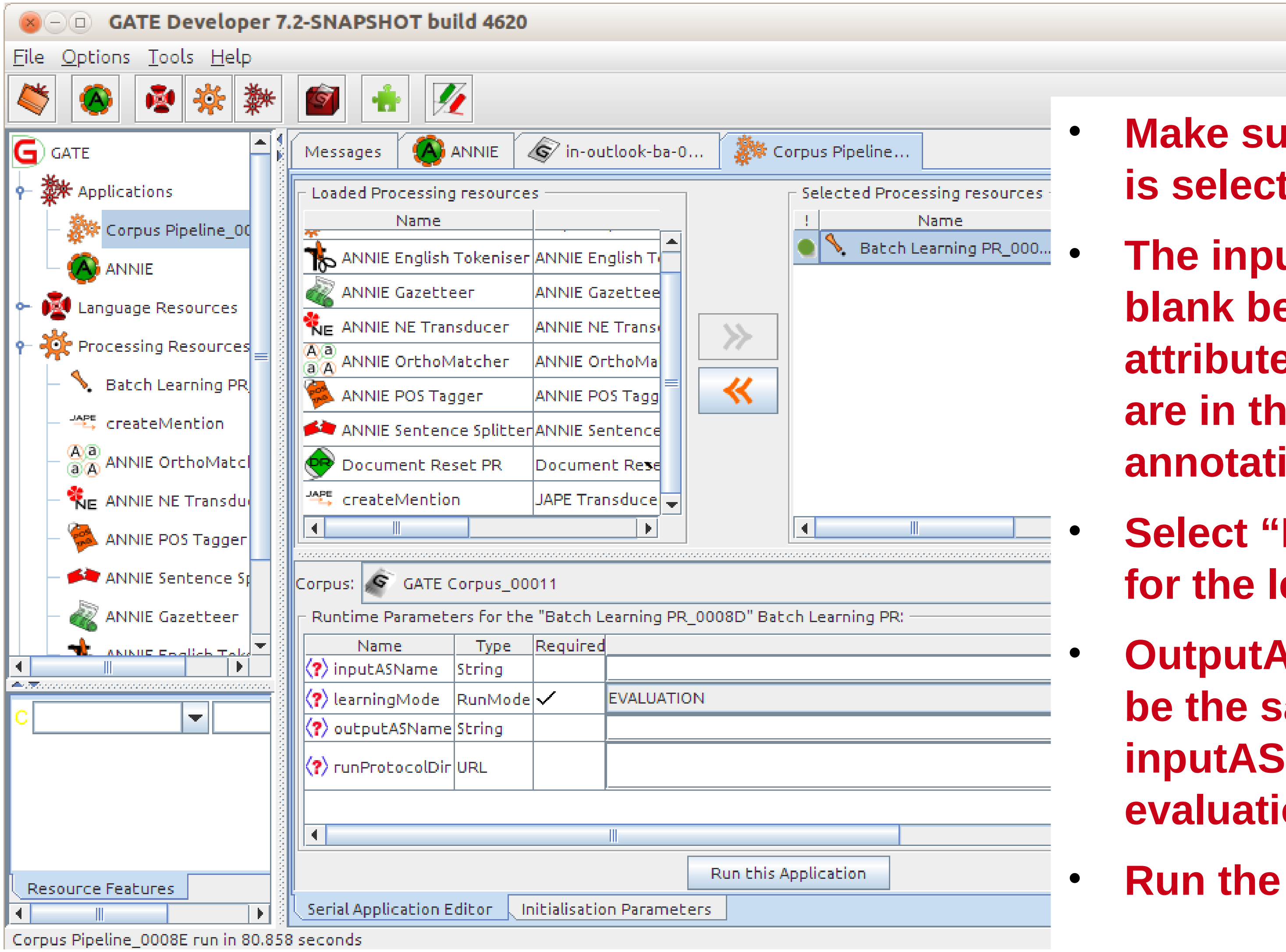


- **Load the "Learning" plugin**
- (We are **not** going to use the "Machine Learning" plugin, as explained earlier)

Creating a learning application

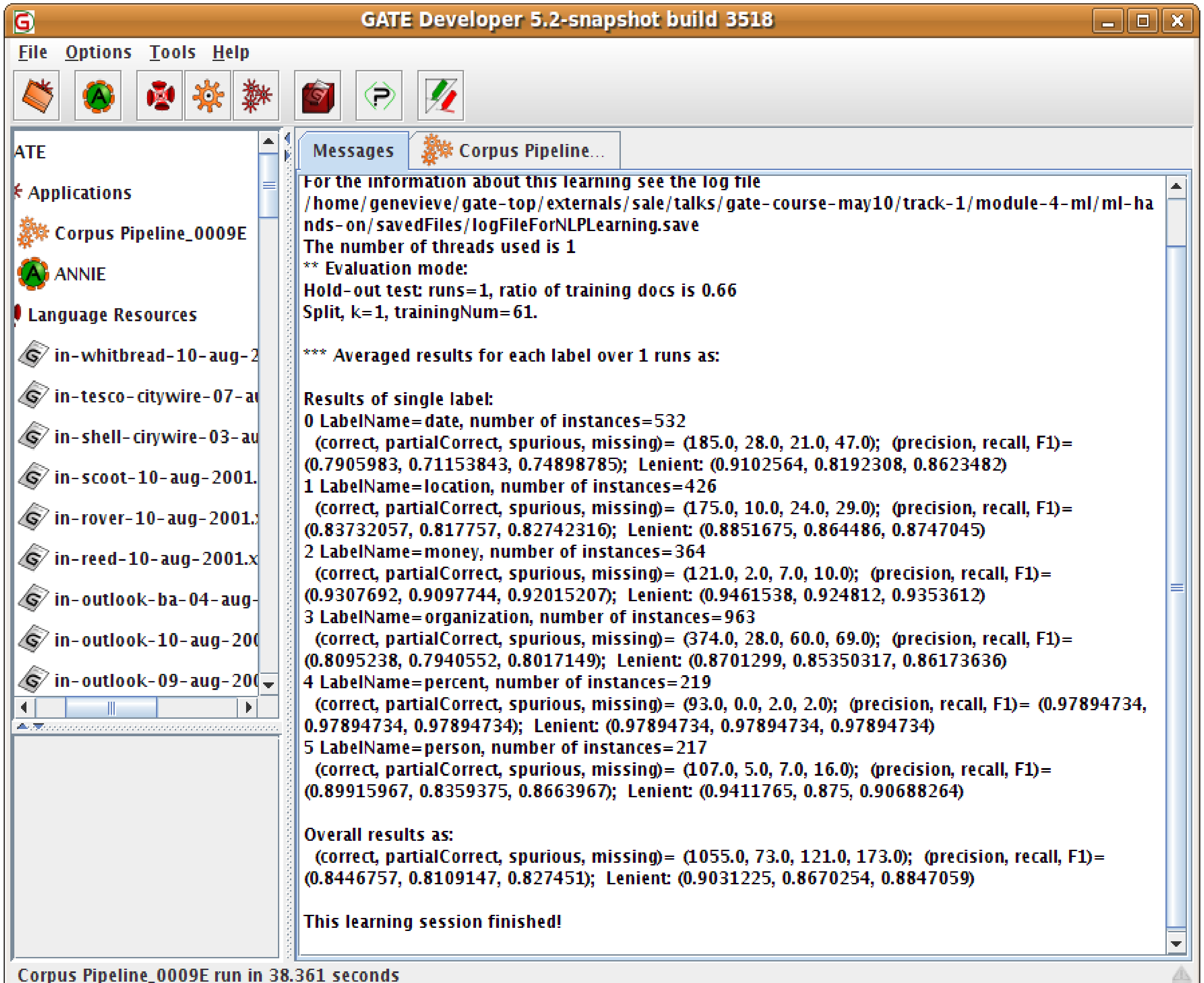
- **Create a "Batch Learning PR" with ner/ner-config.xml as the the configFileURL parameter**
- **Make a new corpus pipeline and put this PR (only!) in it**

Running the application in evaluation mode



- **Make sure the corpus is selected**
- **The inputASName is blank because the attributes and classes are in the default annotation set**
- **Select "EVALUATION" for the learningMode**
- **OutputASName should be the same as inputASName in evaluation mode**
- **Run the application!**

Inspecting the results



- The application may take a few minutes to run
- **When it is finished, switch to the “Messages” tab to examine the results**

How well did we do?

- Here is my previous result:

(precision, recall, F1)= (0.89, 0.75, 0.82)

- These figures look pretty good, but what do they mean?
- Next we will discuss evaluation measures
- Then we will run the PR in different modes
- Then we will see if we can improve these numbers

Evaluation in Machine Learning

Recap of Evaluation in GATE

- Evaluation is an important part of information extraction work
  - We need to find out how good our application is by comparing its annotations to the “right answers” (manually prepared or corrected annotations)
  - Sometimes we need to compare the work of different human annotators, to see how consistent they are
- We use similar functions for both types of evaluation tasks

Evaluation Mode

- We ran the machine learning PR in evaluation mode earlier
- We specified how the PR should run evaluation in the configuration file
- Once we had run the application, we obtained evaluation statistics in the “Messages” tab

What are precision, recall and F1?

- Precision: what proportion of our automatic annotations were correct?
- Recall: what proportion of the correct annotations did our automatic tool create?
- P = correct / (correct + spurious) = tp / (tp + fp)
- R = correct / (correct + missing) = tp / (tp + fn)
- where tp = true positives, fp = false positives, fn = false negatives

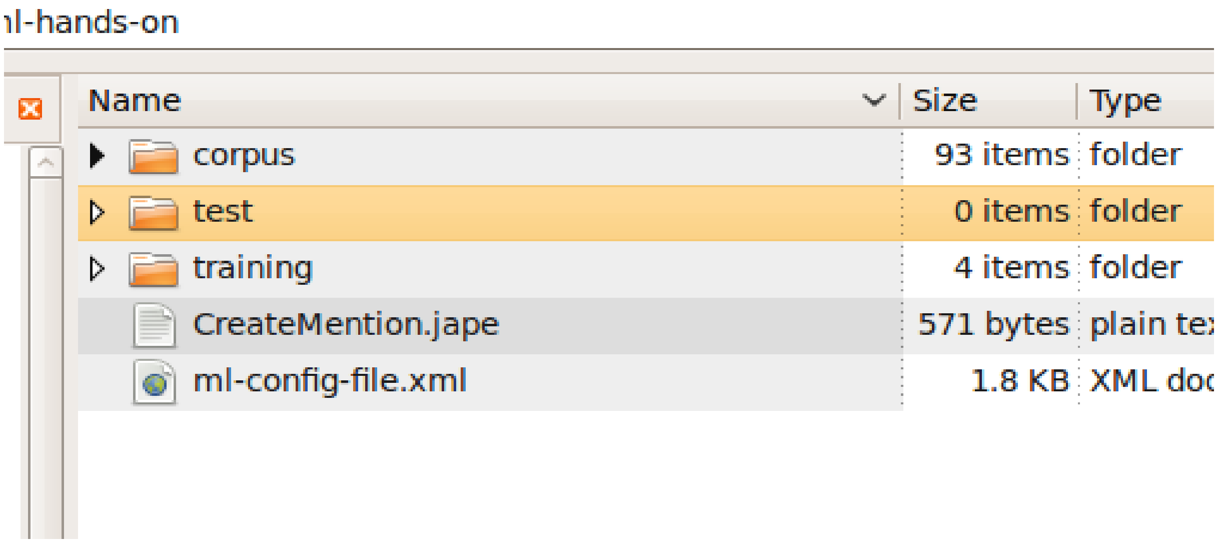
What are precision, recall and F1?

- F-score is an amalgam of the two measures
  - $F_\beta = (1+\beta^2)PR / (\beta^2 P + R)$
  - The equally balanced F1 ($\beta = 1$) is the most common F-measure
  - $F1 = 2PR / (P + R)$
- We can also run our own ML evaluation using the Corpus QA tool—let's do that now

Splitting into training and test corpora

- To tell how well a machine learner is performing, you need to train it and test it on different sets of data
- Evaluation mode does this automatically over “folds” of the corpus
- To see a detailed evaluation, we need to split our corpus into two parts: the training corpus and the test corpus; we will train and apply in separate runs

Saving and splitting the corpus



- **Create new “training” and “test” directories on your computer (somewhere easy to find)**
- **Right click on your corpus, select “Save as XML”, and save the whole corpus in the “training” directory**
- **Use your file manager to move roughly half the documents from “training” into “test” (try to randomise them a little)**

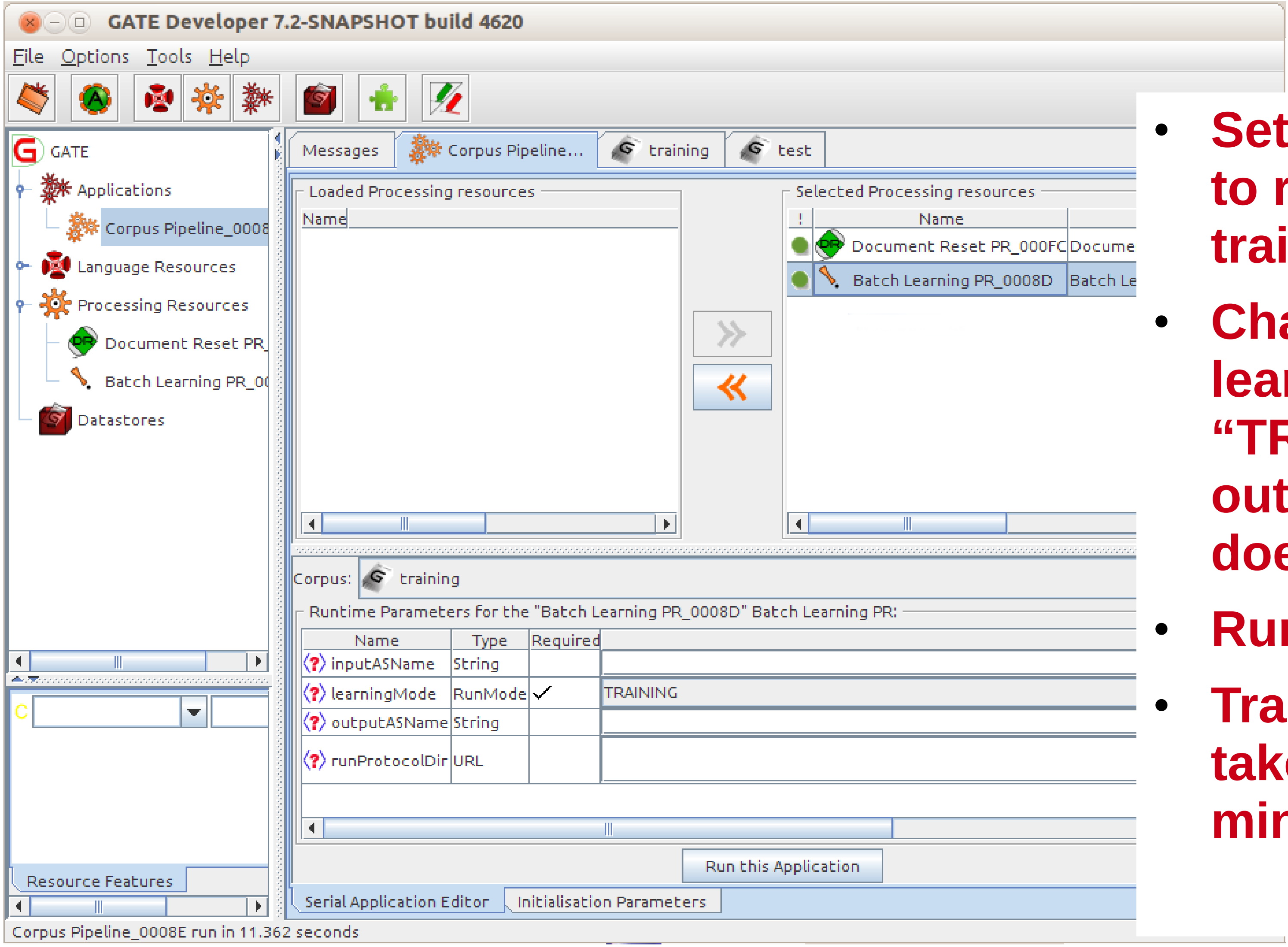
Tidying up

- **Do not close the Batch Learning PR and its corpus pipeline! (We are going to keep using them.)**
- **Close all your open documents and corpora in GATE Developer**
- **Close the modified ANNIE application recursively**
- **Create new GATE corpora called “training” and “test”**
- **Populate each corpus from the appropriate directory (as before, set the encoding to UTF-8!)**

Setting up the application

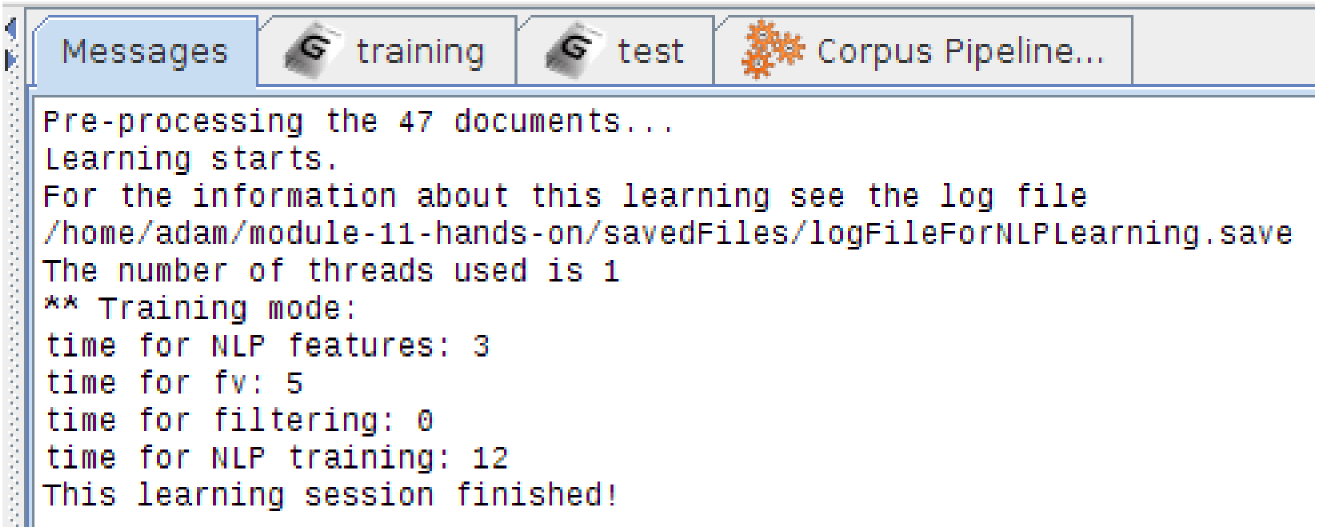
- **Create a Document Reset PR**
- **Add it to the ML pipeline <u>before</u> the Batch Learning PR**
- **Edit the Document Reset PR's <u>setsToRemove</u> parameter to include just “ML”**
- **Edit the setsToKeep parameter to be an empty list**

Running the ML PR in Training Mode



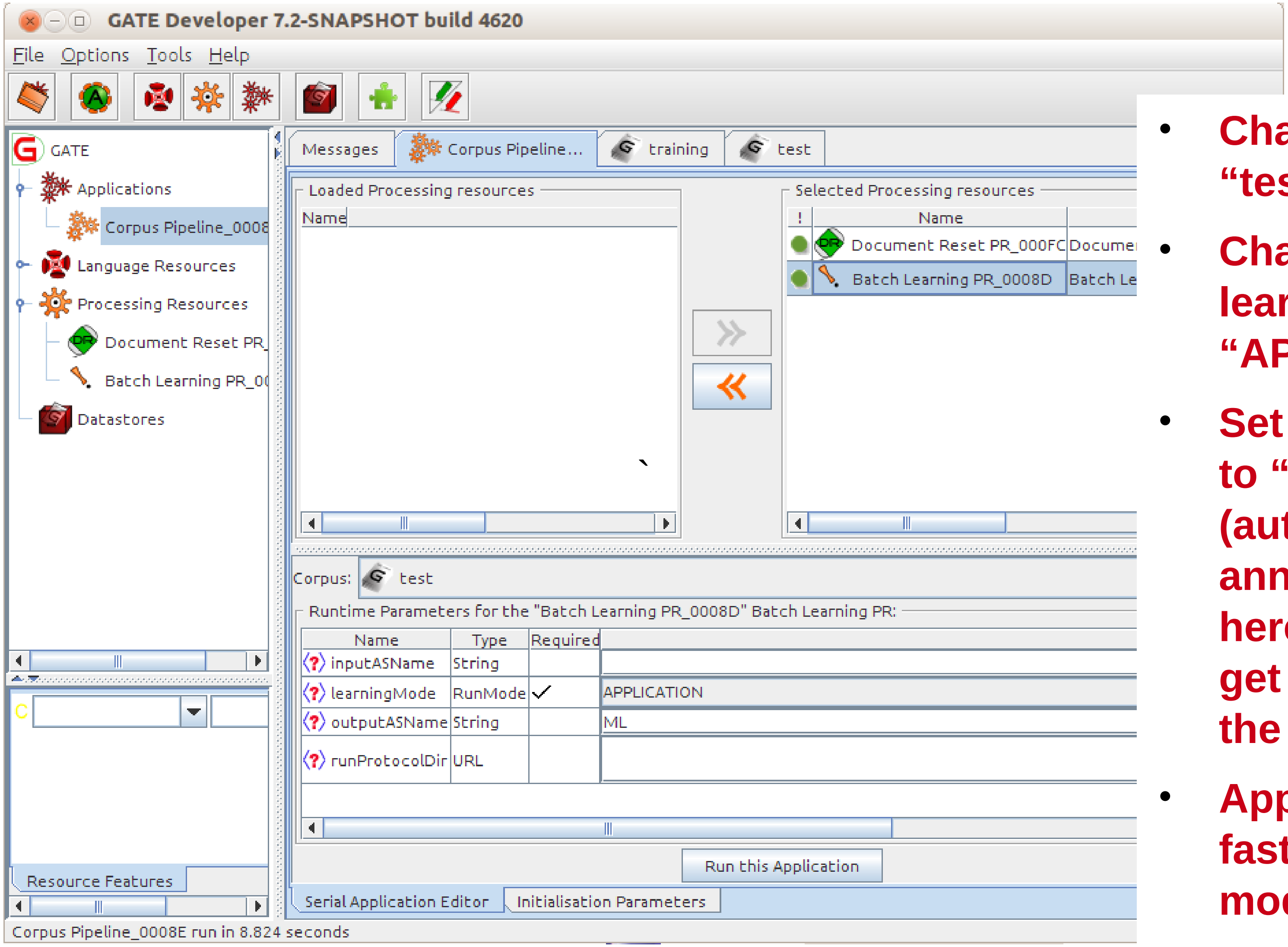
- **Set your pipeline to run on the training corpus**
- **Change the PR's learningMode to “TRAINING” (the outputASName doesn't matter)**
- **Run the pipeline**
- **Training may take a few minutes**

Finished Training!



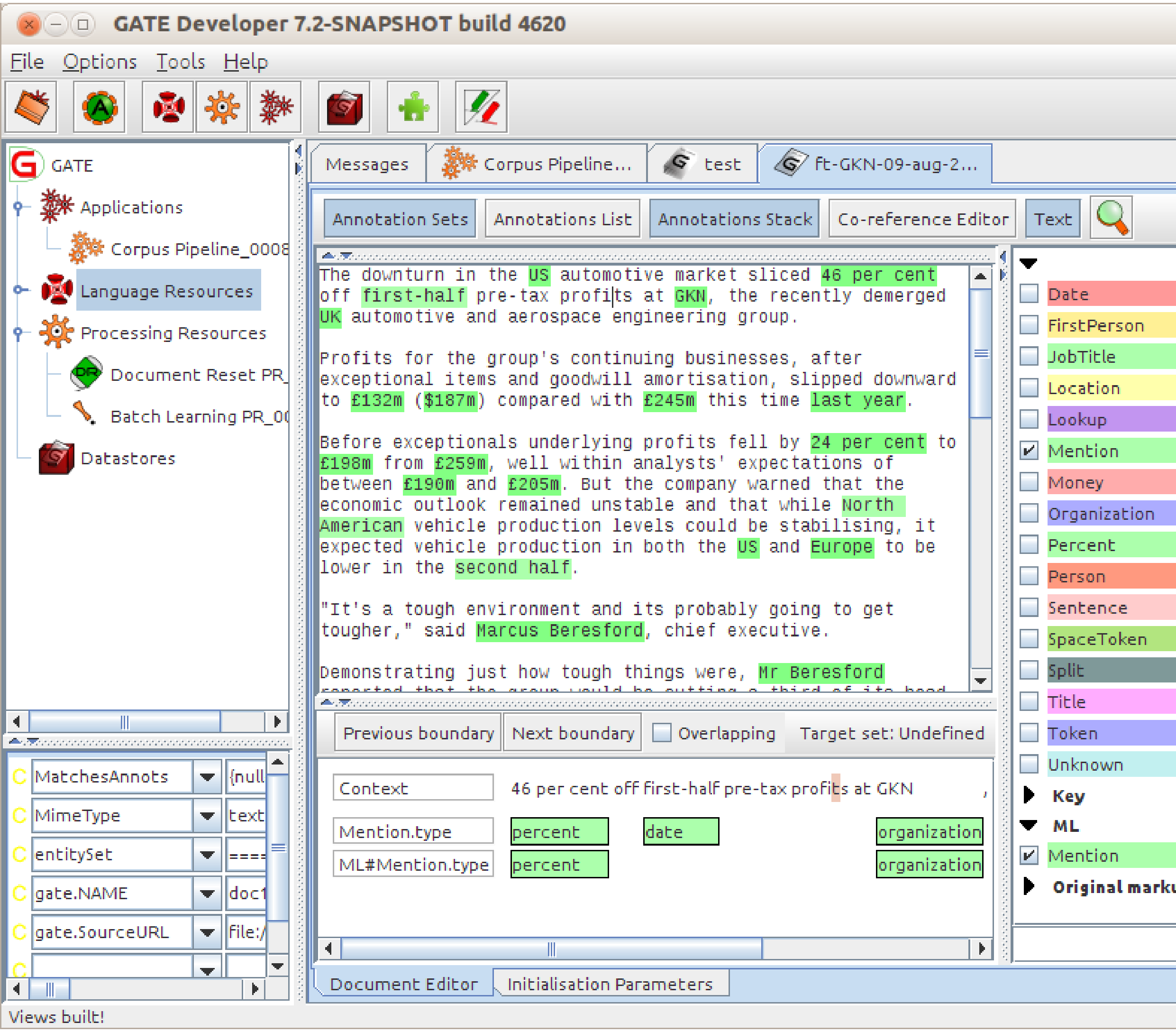
- Because we saved the documents after running our modified ANNIE, they already have the instances and attributes for ML
- This time there are no evaluation results in the messages tab (because we are only training the model)
- Note the “savedFiles” directory beside the XML configuration file
  - Training mode saves the model there
  - Application mode reads it from there
  - The runProtocolDir parameter (in recent versions of GATE) can change the location

Running the ML PR in Application Mode



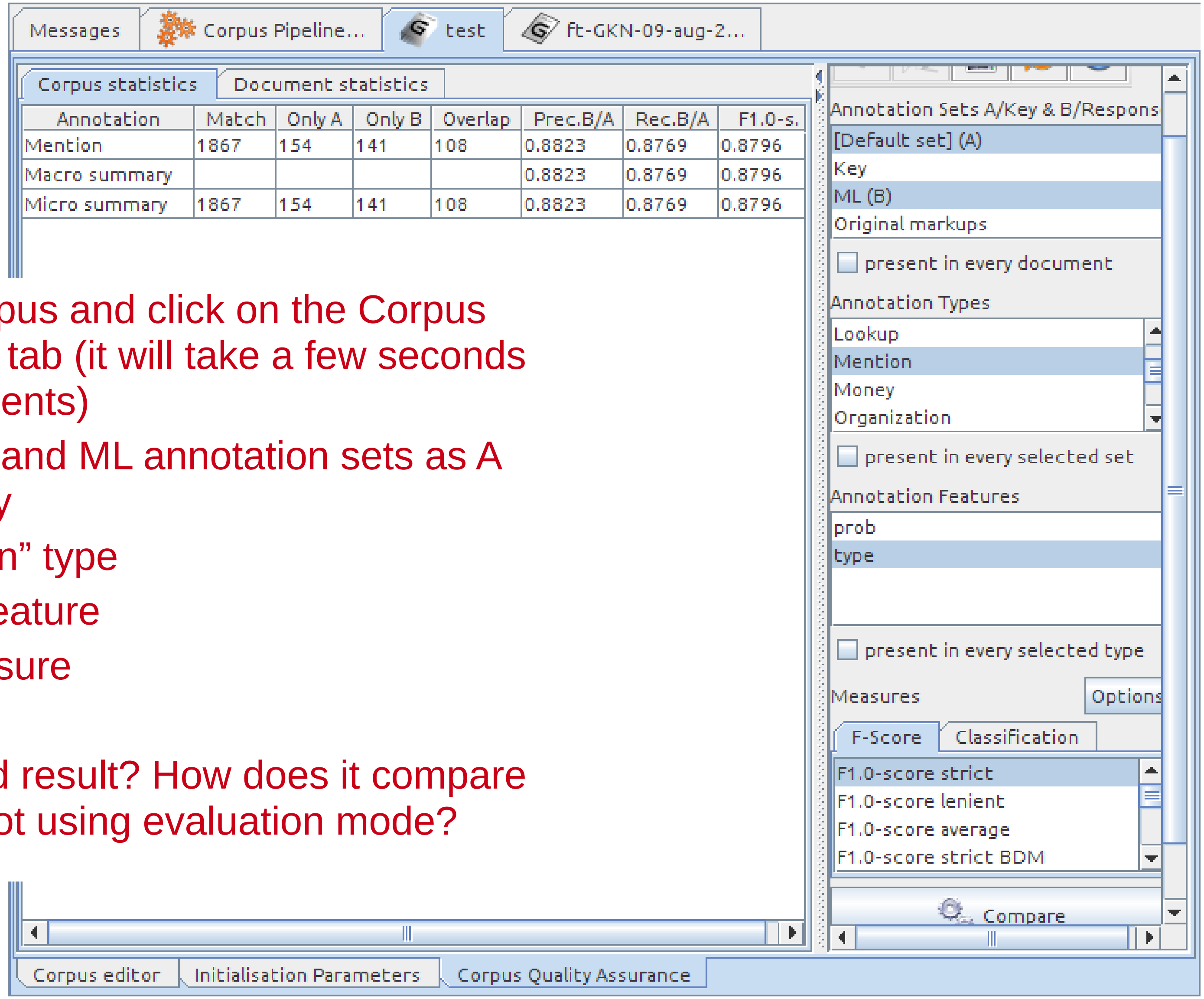
- **Change corpus to "test"**
- **Change learningMode to "APPLICATION"**
- **Set outputASName to "ML": your new (automatic) annotations will go here so they don't get mixed up with the existing ones**
- **Application mode is faster than training mode**

Examining the results of application



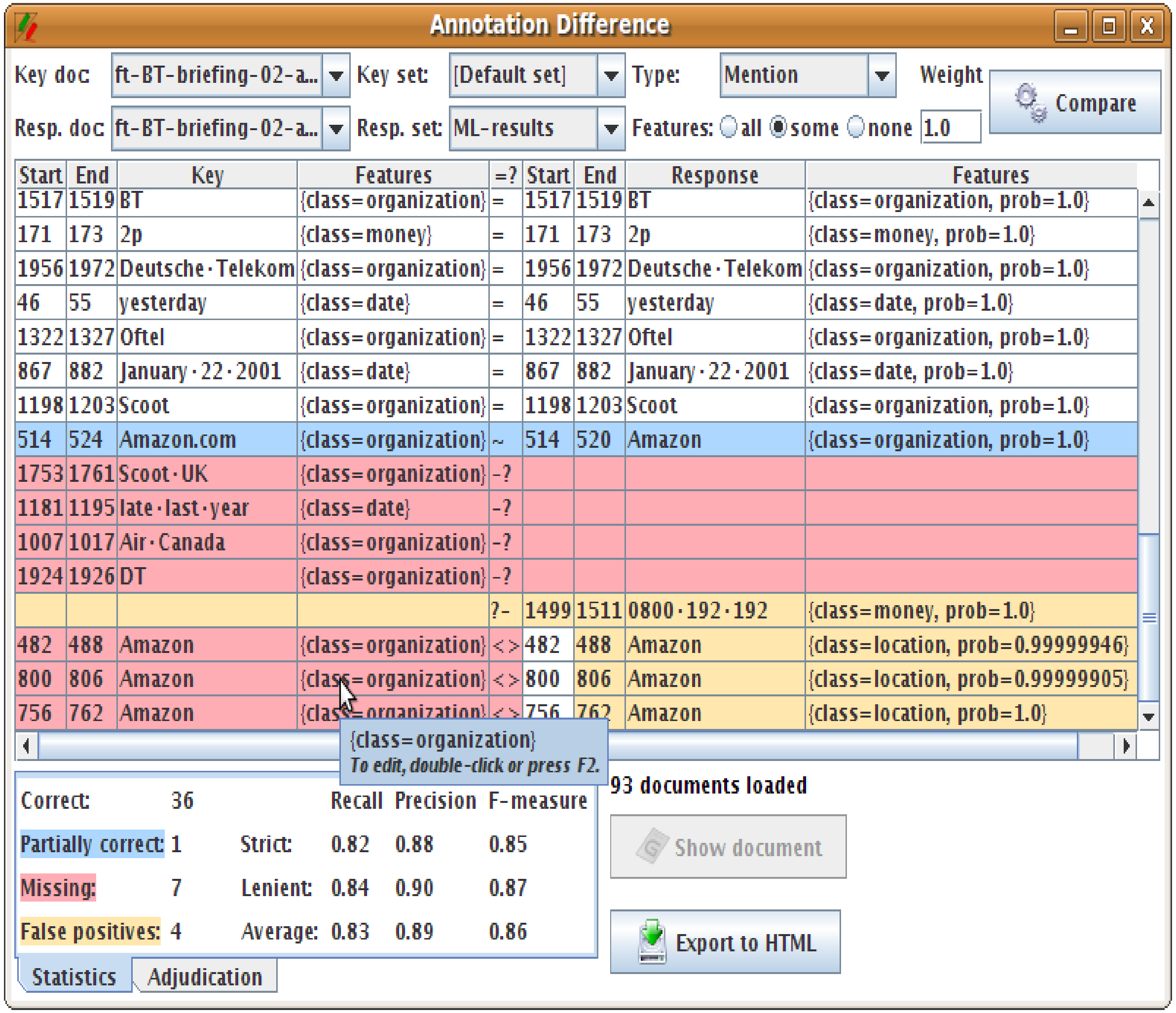
- **Examine a document from the test corpus**
- You should have a new "ML" AS with Mention annotations
- The original Mention annotations (in the default AS) are similar but not always identical!
- The Annotations Stack is good for comparing them
- How similar do they appear to be? Do you think you will get a good result?

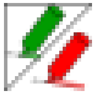
Comparing the Sets with Corpus QA



- Select the test corpus and click on the Corpus Quality Assurance tab (it will take a few seconds to scan the documents)
- Select the Default and ML annotation sets as A and B, respectively
- Select the “Mention” type
- Select the “type” feature
- Choose an F-measure
- Click on Compare
- Did you get a good result? How does it compare to the result you got using evaluation mode?

Using Annotation Diff to examine performance



- **Switch to the "Document statistics" tab**
- **Choose a document**
- **Click on the Annotation Diff icon** 
- What kind of mistakes did your application make?

Using Annotation Diff...

- “Correct”: the response annotation has the right feature and span
- “Partially correct”: response has the right feature and overlapping but not exactly matched span; this counts as correct in the “lenient” scoring
- “Missing”: key annotation+feature is missing from the response (a.k.a. “false negative”)
- “False positive”: response annotation+feature shouldn't be there (a.k.a. “spurious”)

Varying the configuration file

- Now we are going to experiment with varying the configuration file to see if we can produce varied results
- You can edit the configuration file in your favourite text editor
- Make sure you save your changes then **reinitialise the PR** (this reads the file again and updates the configuration used inside GATE)

Confidence Thresholds

```
<PARAMETER name="thresholdProbabilityEntity" value="0.2"/>
<PARAMETER name="thresholdProbabilityBoundary" value="0.42"/>
<PARAMETER name="thresholdProbabilityClassification" value="0.5"/>
```

- Each classifier will provide confidence ratings—how likely is a result to be correct; we must determine how certain is good enough
- Depending on the application we might prefer to include or exclude annotations for which the learner is not too sure
- thresholdProbabilityBoundary and thresholdProbabilityEntity are thresholds for chunk learning
- thresholdProbabilityClassification applies to classification tasks, such as sentiment or genre detection, author identification, language identification