## 1: Sentiment Classification Machine Learning and Real-world Data

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- Machine Learning and Real-world Data
- Three Topics:
  - Sentiment classification thousands of movie reviews
  - Protein sequence analysis hundreds of amino acid sequences
  - Social network analysis thousands of users and links between them
- Practical-based, each with a short lecture introducing the main concepts

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16 sessions, 12 tasks, 8 ticks

- The style of solving tasks in this course is *empirical*.
- You will start from a hypothesis or an idea which you will test

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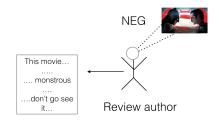
- Then you perform some manipulations on your data
- You observe and record the results
- You need a lab book to record your manipulations, observations and measurements
  - physical book or electronic record

# Today: Evaluative language and sentiment classification

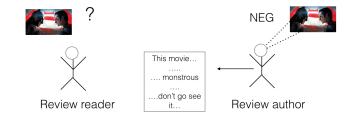
- IMDB (= Internet Movie Data Base) has 4 million titles (2015)
- Reviews are written in natural language by the general public
- Sentiment classification = the task of automatically deciding whether a review is good or bad, based on the text of the review

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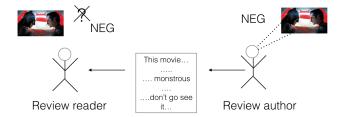
Standard task in Natural Language Processing



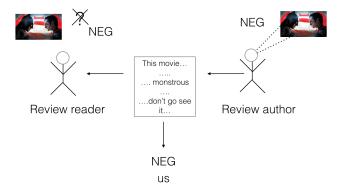
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... He's incredible in fights. ... Also his relationship with Irons, who plays Alfred, is just wonderful in general. Irons was exceptional in the role.

This movie tries so hard... It completely fails on every single level. The movie is tedious and boring with characters that I just did not care about at all. ...

#### Sentiment Lexicon lists 8222 such words

Idea: a review that contains more positive than negative such words is positive

type=strongsubj len=1 wordl=laudably posl=anypos stemmedl=n priorpolarity=positive type=strongsubj len=1 wordl=laugh posl=noun stemmedl=n priorpolarity=negative type=strongsubj len=1 wordl=laugh posl=verb stemmedl=n priorpolarity=negative type=strongsubj len=1 wordl=laughable posl=anypos stemmedl=n priorpolarity=negative type=strongsubj len=1 wordl=laughably posl=anypos stemmedl=n priorpolarity=negative type=strongsubj len=1 wordl=laughingstock posl=noun stemmedl=n priorpolarity=negative type=strongsubj len=1 wordl=laughter posl=noun stemmedl=n priorpolarity=negative type=strongsubj len=1 wordl=laughter posl=noun stemmedl=n priorpolarity=negative type=strongsubj len=1 wordl=lavish posl=adj stemmedl=n priorpolarity=positive type=strongsubj len=1 wordl=lavish posl=verb stemmedl=n priorpolarity=positive

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... He's incredible in fights. ... Also his relationship with Irons, who plays Alfred, is just wonderful in general. Irons was exceptional in the role.

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- incredible positive
- wonderful positive
- exceptional positive

This movie tries so hard... It completely fails on every single level. The movie is tedious and boring with characters that I just did not care about at all. ...

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- try negative
- fail negative
- tedious negative
- boring negative
- care positive

This movie tries so hard... The ending should be exciting and fun and amazing.. and it just... wasn't. It completely fails on every single level. The movie is tedious and boring with characters that I just did not care about at all. ...

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- try negative
- exciting positive
- fun positive
- amazing positive
- fail negative
- tedious negative
- boring negative
- care positive

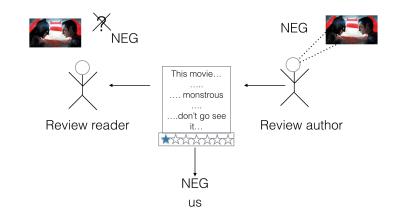
# Tokenisation

- You will look up words from your review document in the lexicon.
- Relationship between strings in the review document and items in the sentiment lexicon is not 1:1
- When words are put together to form a text, some typographic transformations occur:
  - For instance, words at the beginning of a sentence appear in upper case.
  - Words occurring before and after punctuation may be directly attached to the punctuation.
- Therefore, splitting on whitespace is not enough.
- Your code will use a well-known tokeniser to undo the most important transformations.

# **Evaluation**

- How do we know when we have got it right?
- (And I don't mean testing your programs for bugs...)
- The author of the review told us the truth:
  - Explicitly
  - Numerically
  - Star rating
- This is lucky for us, but it's not always so
- We have harvested the star rating along with the review text
- We will use it to calculate a metric called A (accuracy).

# Star rating



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Success can be measured in the number of correct decisions c over all decisions (correct plus incorrect (i)):

$$A = \frac{c}{c+i}$$

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- This metric is called *A* (accuracy).
- We know which decisions are "correct" because we can use the star rating as our definition of truth.

#### Task 1:

- explore the review data (200 documents)
- explore the sentiment lexicon
- write a program that puts the above idea to test
- write a program for using the star ratings to evaluate how well your program is doing

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## **Practicalities**

- 16 lectures (approx 20 minutes) [M, F]
- 16 demonstrated sessions in the Intel Lab: from immediately after lecture to 4:30pm [M, F]
- 12 tasks, 8 ticks
- Ticking during demonstrated sessions (normally the session after work on tick completed)

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Catch-up sessions