Data Mining and Machine Learning

Topic Ana

Peter Jančovič

Objectives

- Statistical modelling of topics
- Identifying topics in a document
  - Latent Dirichlet Allocation (LDA)
- Topic Spotti
  - Salience and Usefulness
  - Example: The AT&T “Ho You?” system

Motivation

- **Example 1**:You are responsible for competitor analysis in a large company. You need to monitor all media for press-releases, news items and other articles relating to your company's product range.
- **Example 2**: ou are given the task of monit for 12 months. You have to identify calls on these are about illegal drug trafficking.
- **Example 3**: You manage a call centre. You are concerned that some staff are being rude to the people that they are calling. You need to monitor all calls for a period of 6 months and detect all instances of 'rudeness'.

Topics

- "your company's product range", "illegal drug trafficking" and "rudeness" are all examples of topics
- A typical document typically covers multiple topics
- Topic Analysing a document into its component topics
- Topic Spotting is about identifying documents that are relevant to a particular topic
- The previous slide is a list of Topic Spotting problems

Topics as "bundles of words"

- For any term *w*, P(*w*) is the probability of *w*
  - Choose a document at random, and then choose a term at random from the document, P(*w*) is the probabilit
  - We know s Law
- If *T* is a topic, P(*w*|*T*) is th al probability of *w* given the topic *T*
  - Choose a document about topic *T* at random, then choose a term at random from the document, P(*w*|*T*) is the probability that the term is *w*

Statistical modelling of topics

- The conditional distribution P($w|T$) is a "bundle of words" model of the topic T
- A typical document is made up of multiple topics
  - Example: e London Marathon
- Latent Dirichlet Allocation (LDA) expresses a document as a combination of topics
- The simplest way to understand LDA is to see how the LDA model generates a document

Documents have multiple topics

Topics include: London, marathons, fund-raising

The race was founded by the former Olympic champion and journalist Chris Brasher and athlete John Disley. It is organised by Hugh Brasher (son of Chris) as Race Director and Nick Bitel as Chief Executive. Set over a largely flat course around the River Thames, the race begins at three separate points around Blackheath and finishes in The Mall alongside St. James's Park. Since the first marathon, the course has undergone very few route changes. In 1992, the finishing post was moved from Constitution truction works. It remained there for twelve years before mo

In addition to being one of over the distance of 26 miles and 385 yards, the IAAF standard for the marathon esta nd originally used for the 1908 London Olympics, the London Marathon is also a sporting festival, third only to the Great North Run in South Shields and Great in Manchester in terms of the number of participants. The event has raised over £450 million for charity since 1981,[2][3] and holds the Guinness world record as the largest annual fund raising event in the world, with the 2009 participants raising over £47.2 million for charity. In 2007, 78% of all runners raised money. In 2011 the official charity of the London Marathon was Oxfam. In 2014, the official charity was Anthony Nolan, and in 2015, it will be Cancer Research UK.

Overview of the London Marathon, Wikipedia, January 2017

Latent Semantic Analysis

- Latent Semantic Analysis can be seen as a method for automatically discovering topics in a corpus
- $W = USV^T$
- In LSA the t lumns of V
- So, a topic is ent vector
- If d is a document and v_i is pic" (column of V), then

$$vec(d) \cdot v_i$$

is a measure of the contribution of the i^{th} topic to d

Latent Dirichlet Allocation

- Consider the document *d*:

  "I eat sandwiches in a deck-chair on the sand by the sea" → "eat sandwiches deck-chair sand sea"

- Intuitively *d* cs, A and B:
  - A: food, c and "sandwiches"
  - B: seaside, correspondi -chair", "sand" and "sea"

- It looks like *d* is made up approximately of 40% topic A (food) and 60% topic B (seaside)

Latent Dirichlet Allocation

- According to LDA, *d* might be generated as follows:
  - Decide number of topics: N=2 "food" (A) and "seaside" (B)
  - Decide the
  - Decide the the topics:

    $P_T(A) = 0.4$, $P_T($
  - For i=1 to M
    - Choose the topic T_i randomly according to P_T
    - Choose word w_i randomly according to $P(w|T)$

Latent Dirichlet Allocation

- So, according to this model the document *d* was generated as follows:
  - *i*=1, $T_1 = A$ ("food"), w = "eat"
  - *i*=2, T_2 = [illegible], w = "wicket"
  - *i*=3, $T_3 = B$ ("seaside"), w = [illegible] "k-chair"
  - *i*=4, $T_4 = B$ ("seaside"), w_4 = "sand"
  - *i*=5, $T_5 = B$ ("seaside"), w_5 = "sea"

Latent Dirichlet Allocation

- This is simple because we know the two topics and their associated word probability distributions
- Given a corpus C and a number of topics N, a much bigger probl … N topics that cover C in s …
- This is the clever part of L …
- LDA uses an "E-M" type algorithm to do this

Latent Dirichlet Allocation

- Basically:
  1. Make an initial estimate of *N* topics (remember, a topic is just a probability distribution over words)
  2. Decomp C into its component topics
  3. Use this decomposition to re-estimate the topic word probability distributions
  4. Go back to 2.

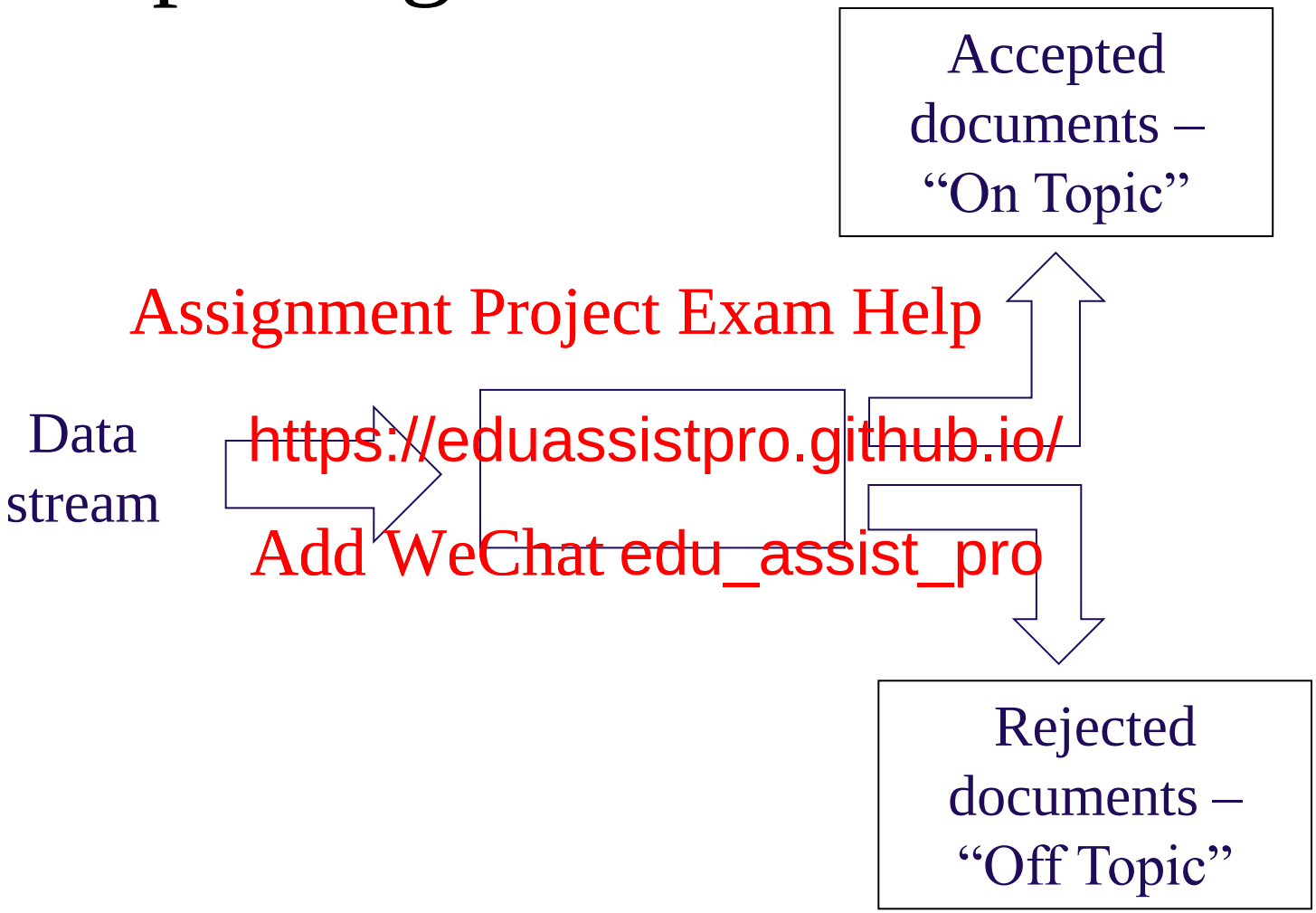
Latent Dirichlet Allocation

- See Edwin Chen's blog "Introduction to Latent Dirichlet Analysis" for an explanation
- The method is called "Latent Dirichlet Allocation" because the e different topics, $P_T(A)$, is ass stribution

Topic Spotting

- Topic Spotting is a type of 'dedicated' IR
  - The task is to find documents that are about a particular topic
  - Corpus from which data is retrieved is dynamic
- Other example
  - Detect all w adio 4 broadcasts
  - Find all documents written Bronte
  - Find all requirements in new EU railway legislation
- Topic Spotting vs IR
  - Because a topic is richer than a query we can calculate probabilities $P(t|T)$ and not just $IDF(t)$

Topic spotting



TF-IDF weights

- Recall the definition of the TF-IDF weight for a term *t* relative to a document *d:*

$$w_{t,d} = f_{t,d} \times IDF(t), \text{where, } IDF(t) = \log\left(\frac{ND}{ND_t}\right)$$

- *IDF*(*t*) indicate minating bet documents
- $f_{t,d}$ ensures that *t* occurs sufficiently often to be useful
- For Topic Spotting we can define a more sophisticated criterion to identify words that are indicative of a given topic

Usefulness

- Given a term ***t*** and a topic ***T***, define the usefulness of ***t*** (relative to ***T***) by:

$$U(t) = P(t|T)\log\frac{P(t|T)}{P(t)}$$

- If $\log\frac{P(t|T)}{P(t)}$ is large t is [illegible] stic of the topic

- If $P(t|T)$ is large, then t occurs sufficiently often "on topic" to be useful for topic spotting

Usefulness and IDF

- Recall $IDF(t) = \log\left(\frac{ND}{ND_t}\right)$
- Given a set $S_{t'} = S_t \cup S_{t'}$, where S_t is the set of documents that contain t and $S_{t'}$ is the set of documents that do not
- Then $P(t) = P(t \mid S_t)P(S_t) + P(t \mid S_{t'})$

$$= P(t \mid S_t)P(S_t) = P(t \mid S_t)\frac{ND_t}{ND}$$

Usefulness and IDF

- Hence

$$\frac{P(t \mid S_t)}{P(t)} = \frac{ND}{ND_t}, \text{ and } IDF(t) = \log\left(\frac{P(t \mid S_t)}{P(t)}\right)$$

Usefulness and IDF

- $IDF(t) = \log\left(\frac{P(t \mid S_t)}{P(t)}\right)$ is a measure of how useful the term t is for general information retrieval (or for retrieving do t?)

- So, $\log\left(\frac{P(t \mid T)}{P(t)}\right)$ is a meas usefulness of t for retrieving documents about topic T

‘Salience’

- Similarly, given a term ***t*** and a topic ***T***, define the salience of ***t*** (relative to ***T***) by:

$$S(t) = P(T \mid t) \log \frac{P(T \mid t)}{P(T)}$$

- Using Bayes’ Theorem (h easy to establish a relationship between sali sefulness

$$P(T \mid t) = \frac{p(t \mid T) P(}{p(t)}$$

Salience and Usefulness

$$S(t) = P(T \mid t) \log\left(\frac{P(T \mid t)}{P(T)} \right)$$

$$= \frac{p(t \mid T)P(T)}{p(t)} \log\left(\frac{p(t \mid T)}{P(T)p(t} \right)$$

$$= \frac{P(T)}{p(t)} p(t \mid T) \log\left(\frac{p(t \mid T)}{p(t)} \right) = \frac{P(T)}{p(t)} U(t)$$

Salience and Usefulness

$$S(t) = \frac{P(T)}{p(t)} U(t)$$

- Now, T is th. Therefore

$$S \quad \frac{1}{\quad}$$

Salience and Usefulness

- So, main difference between Salience and Usefulness is that to have high usefulness, a term must occur frequently
- Sometimes t useful words for a topic are n immediately suspect:
  - E.G. For Weather Forecast spotting, “north”, “south”, “east” and “west” turned out to be more ‘useful’ than “rain” and “sun” – why?

Example

- A term *w* occurs:
  - t_1 times in documents about topic *T*
  - t_2 times in documents which are not about topic *T*
- Total number of terms:
  - in documen
  - in documen
- The corpus contains C_1 documents about *T* and C_2 documents not about *T*
- Then
  - $P(w|T) = t_1/N_1$, $P(w|not\text{-}T) = t_2/N_2$
  - $P(w) = P(w|T)P(T) + P(w|not\text{-}T)P(not\text{-}T)$

$$= \frac{t_1 C_1}{N_1(C_1 + C_2)} + \frac{t_2 C_2}{N_2(C_1 + C_2)} = \frac{t_1 N_2 C_1 + t_2 N_1 C_2}{N_1 N_2 (C_1 + C_2)}$$

Example

- A term *w* occurs:
  - $t_1 = 150$ times in documents about topic *T*
  - $t_2 = 230$ times in documents which are not about topic *T*
- Total number of terms:
  - in documen *500*
  - in documents not about topi *3,100*
- Suppose that only 10% of are "on topic"
- So:
  - $P(w|T)=0.012$, $P(w)=0.0102$, $\log(P(w|T)/P(w)) = 0.0706$
  - $U(w) = 0.000847$
  - $S(w) = (P(T)/P(w)) \times U(w) = (0.1/0.0102) \times 0.000847 = 0.0083$

Application to Topic Spotting

1. Start with a training corpus of documents d_1,..., d_N. Each d_n could be a separate document, or a section (e.g. paragraph) from the same document.
2. For each n -topic (T) or off-topic (*not-T*
3. Apply stemming and sto oval if required
4. Identify the set of terms (the vocabulary) in the corpus: w_1,..., w_V.
5. For each v, calculate $U(w_v)$ – the usefulness of w_v for the topic T.

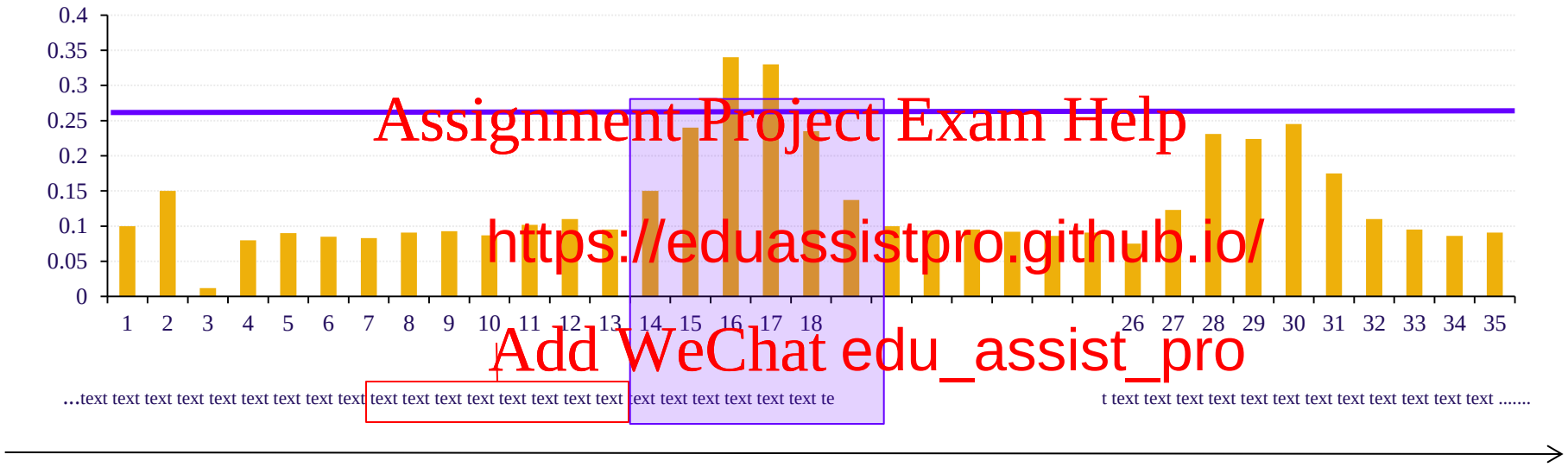
Application (continued)

6. If required, choose a threshold X and discard any terms with usefulness less than X
7. For each document d in the training set:
   - Let v_1,..., $v_{I(n)}$ be the terms in d_n
   - Calculate $AU(d_n) = \frac{1}{I(n)} \sum_{i=1}^{I(n)} U(v_i)$
   - $AU(d_n)$ is the average usefulness of terms in d_n

Application (continued)

8. For a threshold W define a classification rule by:
   - If $AU(d_n) > W$, then d_n is classified as "topic"
   - If $AU(d_n) \leq W$, then d_n is classified as "not-topic"
9. Choose a suit training documents. For example qual Error Rate
10. Classification: Given a new d
    - Calculate $AU(d)$
    - Classify d as "topic" if $AU(d) > W$, otherwise d is "not-topic"

Topic Spotter



Spotting topics in speech

- First convert audio stream into a text stream using automatic speech recognition
- Consider overlapping sections of text corresponding to, say, 30 seconds on the application)
- Calculate the Average (or fulness or Average (or Total) Salience of words in the section of text for the topic
- Signal whenever this value exceeds a threshold

Example

- The AT&T "How May I Help You?" system
- Task: to understand what AT&T customers' messages are about sufficiently well to connect them to the correc
- Services can be human op o deal with a specific problem or speak language) or automated services.
- Look HMIHY? Up on the web

AT&T How May I Help You?

Salient word list

Service 1

Service 2

Service 3

Service 15

AT&T How May I Help You?

- HMIHY? Treats telephone network services as topics or documents, to be detected or retrieved
- Example salient words:

Word				Salience
Difference				1.29
Cost	3.39			1.28
Rate	3.37			1.23
Much	3.24			1.23
Emergency	2.23		Charge	1.22
Misdialed	1.43		Home	1.13
Wrong	1.37		Information	1.11
code	1.36		credit	1.11

Allen Gorin, "Processing of semantic information in fluent spoken language, Proc. ICSLP 1996

HMIHY Demonstrations

- See http://www.research.att.com/~algor/hmihy/samples.html

Summary

- Topics
- Modelling a document as a mixture of topics
- Latent Diric
- Topic spotti
- Salience and usefulness
- How May I Help You?