Information Nutrition Labels

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Research Areas

Multi-lingual Argument Retrieval

Rumour Verification

Information Nutrition Labels

Research Areas

Multi-lingual Argument Retrieval

Argument Retrieval

Idea: Given a user query the search engine must retrieve arguments instead of documents

Argument: Claim + Premises

Claim: Brexit will have a positive impact on UK's economy

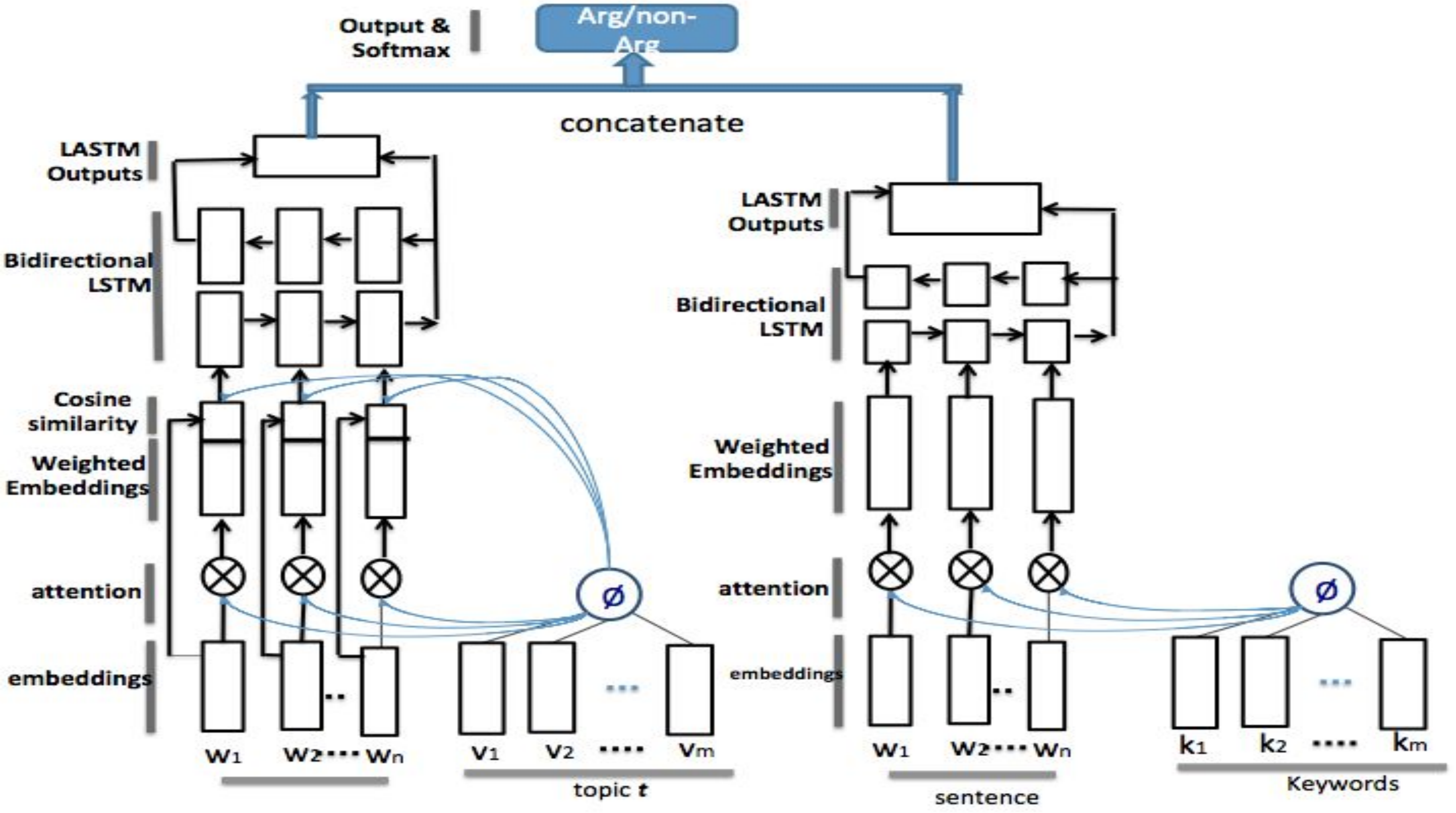
Premise: Goods exports from the UK to other countries rose 3.4% between June and July 2016

User query: What are the positive impacts of Brexit on UK's economy

Argument Retrieval (con)

Advantage over normal document retrieval: help users in decision making by providing pro and con premises to claims

E.g. a banker may perform a critical investment, a company owner may decide on a growth strategy, a journalist may write a report or perform fact checking for a critical political statement that is suspected to be a fake news, etc.


Output & Softmax
Arg/non-Arg
concatenate
LASTM Outputs
Bidirectional LSTM
Cosine similarity
Weighted Embeddings
attention
embeddings
ø
w1 w2 .... wn
v1 v2 .... vm
topic t
LASTM Outputs
Bidirectional LSTM
Weighted Embeddings
attention
embeddings
ø
w1 w2 ... wn
k1 k2 .... km
sentence
Keywords

Multi-lingual Argument Retrieval

Aim: Users might want to compare English arguments to arguments written in other languages (comparing viewpoints)

Step 1: Query is posted in e.g. English

Step 2: English documents are found (those containing relevant arguments)

Step 3: Foreign documents that are comparable to the English documents are determined

Step 4: Either performing argument detection on foreign documents or argument projection (projecting English arguments by finding their translations on the target side)

Research Areas

Rumour Verification

Rumours

Some examples:

True rumour: "10 people dead in Charlie Hebdo according to witnesses"

False rumour: "GERMAN NEWS REPORT: Co-Pilot of Germanwings Airbus Was MUSLIM CONVERT …'Hero of Islamic State'?"

Unverified rumour: "Police in Ferguson claimed that Mike Brown had been involved in a robbery"

Rumours

[depth=0] **u1:** These are not timid colours; soldiers back guarding Tomb of Unknown Soldier after today's shooting #StandforCanada –PICTURE– **[support]**

[depth=1] **u2:** @u1 Apparently a hoax. Best to take Tweet down. **[deny]**

[depth=1] **u3:** @u1 This photo was taken this morning, before the shooting. **[deny]**

[depth=1] **u4:** @u1 I don't believe there are soldiers guarding this area right now. **[deny]**

[depth=2] **u5:** @u4 wondered as well. I've reached out to someone who would know just to confirm that. Hopefully get response soon. **[comment]**

[depth=3] **u4:** @u5 ok, thanks. **[comment]**

Rumour verification through stance

Performing rumour verification based on stance (support, deny, question, comment)

How?: Use HMM (standard) and time-based HMM

System	Precision	Recall	F_1
B1	0.650	0.481	0.553
B2	0.661	0.481	0.557
λ	**0.747**	0.765	0.756*
λ'	0.690	**0.963**	**0.804***
majority-vote	0.059	0.025	0.035

Research Areas

Information Nutrition Labels

Information Nutrition Labels

Motivation:

- Online news content is immense in size and its sources of are very diverse
- For the readers and other consumers of online news who value balanced, diverse and reliable information, it is necessary to have access to methods of evaluating the news articles they are presented with

Food consumption:

- Consumers are presented with huge variety of food alternatives and face the challenge to decide what is good for their health
- This is why food packages come with nutrition labels that guide the consumers in their decision making

Information Nutrition Labels

First studies:

- Fuhr et al. (2018) discuss the idea of implementing information nutrition labels for news articles
- Propose to label every online news article with information nutrition labels that describe the ingredients of the article and give readers a chance to make an informed judgment about what they are reading
- 9 different information nutrition labels: factuality, readability, virality, emotion/sentiment, opinion/subjectivity/objectivity, controversy, authority/credibility/trust, technicality and topicality
- Gollub et al. (2018) categorize these labels into fewer dimensions to provide easy understanding

Information Nutrition Labels

Our contribution:

- Implementing information nutrition labels suggested by related work
  - provide a basis for evaluating (1) how well labels describe the online news content and (2) for investigating how useful they are to real users for making decisions about whether to read the news and whether to trust its content
- Investigating new labels
- Investigating presentation
  - To avoid biasing the user in any way with respect to the consumption of an article, the information is solely presented but not interpreted
- Implementing and designing users interfaces in form of mobile apps and Internet Browser plugins

Implementing proposed labels

Sentiment

- News articles may contain sentimental sentences to address the readers feelings and emotions
    - E.g. to capture the reader and make her belief about what is written in the article
- Sentimental articles may have degraded quality
- Our preliminary investigation shows that fake news articles are more sentimental than non-fake ones (average: 0.12 vs. 0.07)

Sentiment

- We use existing API to determine the sentiment score of each news article (Hayden and Smet (2018)
- We compute sentiment scores for each sentence in the article
- The sentiment score can vary from -1 (negative) to +1 (positive)
- We are interested in whether the article is sentimental or not thus use only absolute values
- Label score to show: average absolute sentiment value over the sentences

Objectivity

- Analogues to sentiment the objectivity is a important label for news articles
- Articles that are not objective may contain authors viewpoints/interpretations
- Such articles may again have degraded quality vs those that are highly objective
- Again our preliminary investigation shows that e.g. fake articles are less objective than non-fake ones (average: 0.55 vs. 0.62)

Objectivity

- Analogues to sentiment we use the same API to compute for a news article its objectivity score (Hayden and Smet (2018)
- API computes subjectivity but objectivity = 1 - subjectivity
- The subjectivity score can vary from 0 (not subjective) to +1 (very subjective)
- Label score to show: 1 - average subjectivity score over all sentences

Ease of reading

- Schwarm and Ostendorf (2005): the readability level is used to describe the educational level a reader needs to understand a text
- Less quality text might be written in a way to be consumed by less educated readers
- E.g. fake articles tend to require lower educational level than non-fake ones (0.6 vs 0.4)

Ease of reading

- Related work has investigated machine learning along with feature engineering: lexical, structural, and heuristic based features
- We implemented a random-forest approach with those features
- Accuracy on texts written by students in Cambridge English examinations: 73%
- The classifier predicts five different levels of readability varying from A2 (easy) to C2 (difficult)
- Label score to show: We map these values to percentages so that A2 becomes 100% (easy to read) and C2 becomes 20% (difficult to read)

Investigating new information nutrition labels

Source popularity

- Gives an indication how popular a source that is publishing the news article is
- Assumption: less popular sources should be less reliable or trusted

- Based on domain name
    - e.g. bbc.com, theguardian.com, nj.com

- Based on related Twitter account
    - quite often the twitter account is found with basic approach
    - otherwise, ignored

Source popularity

- Alexa Rank
- website traffic
  - unique visitors
- Page Rank
- links between websites
  - authority, prestige
- Web-of-Trust
- crowdsourced reputation system
  - scams, malwares, etc
- Twitter Account
- followers, favorited and listed counts

Label score to show: averaged score of all above

Article popularity

- Indicates how popular the article is in Twitter (shared)
- Based on this a reader sees that she is not the only one consuming it
- Search for article in Twitter (title)
- Count number of tweets and retweets (24H)
- Label score to show: Popularity = a log (x + 1)

(a=73, reference article 23 times/hour, x frequency of distribution per hour of the article currently analysed)

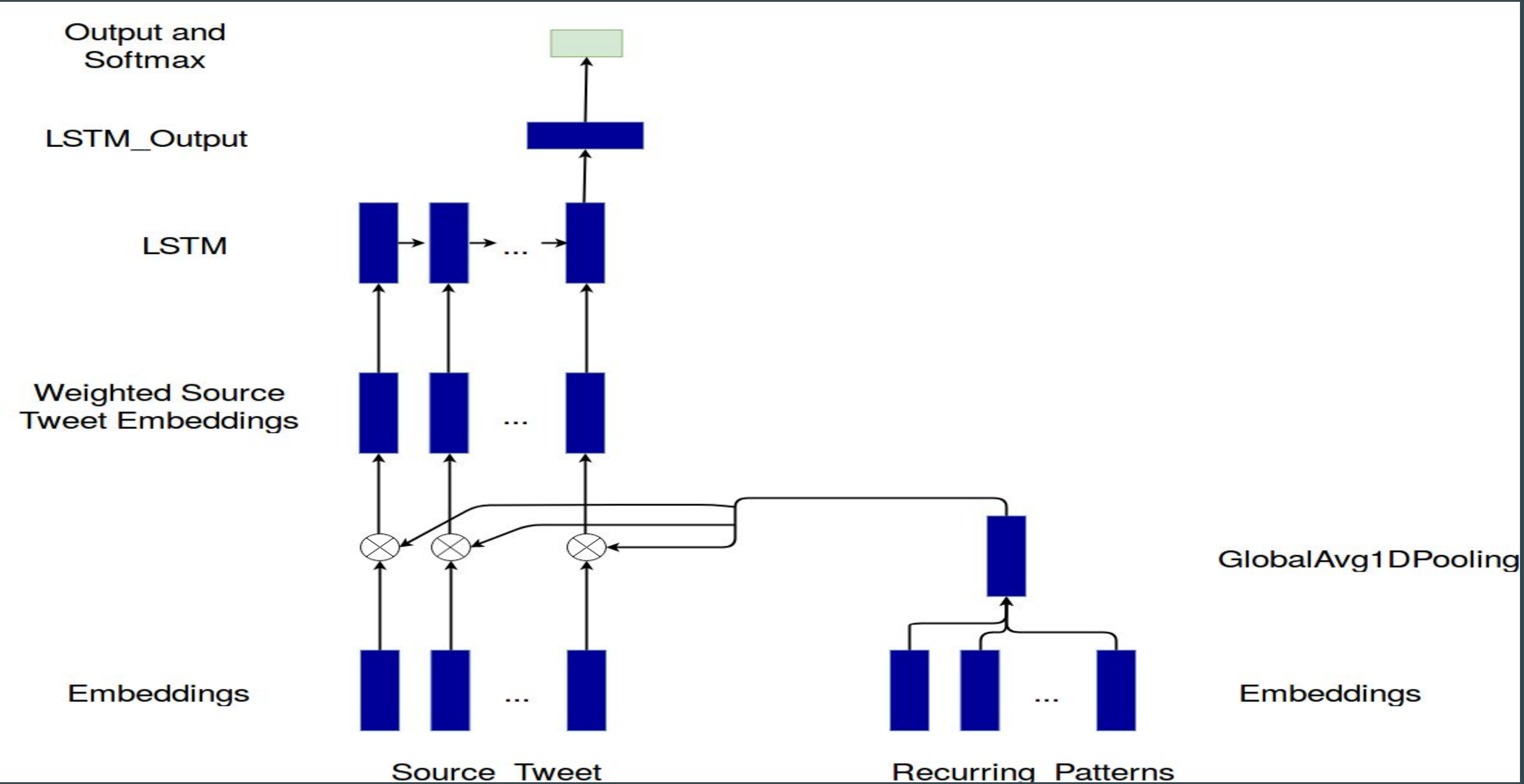
Pollutant or better name?

- Determine the non-trusted users distributing the news article
- Motivation: Fake News articles tend to have a different "discussion behaviour" than confirmed truths

Pollutant: Ground Truth Data

- Usage of Rumoureval and PHEME dataset
- Extraction of potential reliable/non-reliable tweets discussing events
- Using the knowledge from above to grade the users (network analyses)

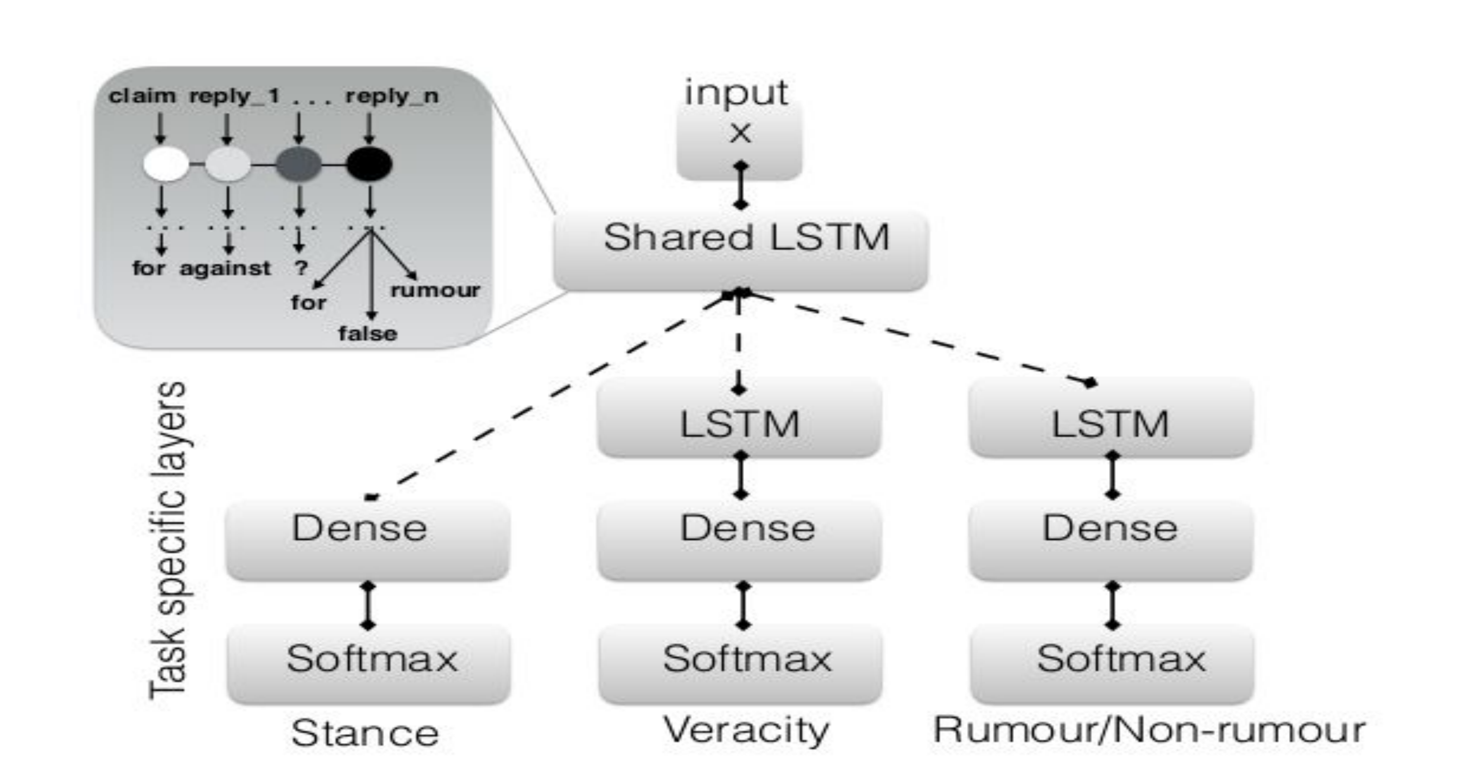
Pollutant: Network for veracity classification



Pollutant: Veracity Classifier Evaluation

- Fixed test dataset with 28 source tweets and its veracity label
- Inner-Attention-Based Neural Network achieved **60.7 %** accuracy
- Best previous system with Multi-Task-Learning model achieved **57.1 %** accuracy

Pollutant: Reference - Multi-Task-Learning



Investigating Presentation

Design

- Monochromic colours work as well as traffic light colours with nutrition labels
  (Aschemann-Witzel et al., 2013)

- Simple layouts using icons, colours and some text are easiest to get
  (Antúnez et al., 2013; Campos et al., 2010; Cowburn & Stockley, 2005; Hersey et al., 2013; Roberto & Khandpur, 2014)

- Complex numbers or a lot of text should not be used
  (Campos et al., 2010; Cowburn & Stockley, 2004)

- Different labels should be represented in the same way
  (Ducrot et al., 2016; Kelley et al., 2009)

- Different labels should be separated from each other
  (Goldberg et al., 1999; Gestaltgesetze)

Design

Flipping card for every feature

- Front: icon and name
- Back: Overall score and sub-features

→ no information overload

Barcharts to represent value

- Percentage
- Easy to understand?
- Normalizable for each feature (0-100%)

Design

Size and position

- Top right corner
- Does not overlap with the news article

Colour

- Shades of blue
- Meaning: trust, security and honesty

Same design for every feature with separating lines between features

Investigating Implementation Formats


politics
Trump was 'all snarls' in public, bu
in private at NATO, diplomats say
NewsCheck
Source Popularity
Virality
Ease of Reading
Sentiment
Objectivity
Bias

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