What is Relevant in a Text Document?

An Interpretable Machine Learning Approach

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Word2Vec

Word2Vec

- \cdot Is an approach to learn vector representations of words
- Using the context words to create the initial vectors

Skipgram

- Is better to represent infrequent words
- Nearby context words have higher weight
- Trained by each context against the word

CBOW

- Predicts a word given a window of context words
- Order of context words has no weight
- Trained by each word against its context

Layer-Wise Relevance Propagation

Identifying Relevant Words



Figure 1: Diagram of a CNN-based interpretable machine learning system

Needs a vector-based word representation and a neural network

Step One Compute input representation of text document

Step Two Forward-propagate input representation

Step Three

Backward-propagate using the layer-wise relevance propagation

Step Four

Pool the relevance score onto the input neurons

Computing the input representation of a text document

Words	Vectors
the	[0.035, -0.631,
cat	[0.751, -0.047,
sat	[0.491, 0.002,
on	[-0.181, -0.086,
the	[0.035, -0.631,

Table 1: CBOW vector example

Forward-propagate the input representation until the output is reached

- We begin with our D×L matrix-representation of the document
 - D is the embedding dimension
 - L is the document size
- The convolutional layer produces a new representation of F features maps of length L H + 1
- ReLU is applied element wise
- Features maps are pooled by computing the maximum over the text sequence of the document
- The maxpooled features are fed into a logistic classifier

ML Model	Test Accuracy (%)	
CNN1 (H=1, F=600)	79.79	
CNN2 (H=2, F=800)	80.19	
CNN3 (H=3, F=600)	79.75	

Table 2: Performance of different CNN models

Backward-propagate using the layer-wise relevance propagation

- Delivers one scalar relevance value per input variable, input data point and possible target class
- Redistributes the score of a predicted class back to the input space
- The Neuron that had the maximum value in the pool is granted all the relevance

Pool the relevance score onto the convolutional layer

•
$$R_{(i,t-\tau)\leftarrow(j,t)} = \frac{Z_{i,j,\tau}}{\sum_{i,\tau} Z_{i,j,\tau}}$$

- Similar to the Equation used for LRP
- More complex due to the convolutional structure of the layer

Pool the relevance score onto the input neurons

- $R_{i,t} = \sum_{j,\tau} R_{(i,t) \leftarrow (j,t+\tau)}$
- The Word that had the maximum value in the pool is granted all the relevance

Identifying Relevant Words



Figure 2: Diagram of a CNN-based interpretable machine learning system

Obtaining relevance over all dimensions of word2vec

- $R_t = \sum_i R_{i,t}$ pool relevances over all dimensions
- $\forall_i : d_i = \sum_t R_t \cdot x_{i,t}$ condense semantic information
- $\forall_i : d_i = \sum_t R_{i,t} \cdot x_{i,t}$ build document summary vector without pooling

BoW/SVM as Baseline

Bag of Words

- · Documents are represented as vectors
- Each entry is TFIDF of a word in the training vocabulary

Support Vector Machine

- Hyperplanes are learned to separate classes
- $\cdot\,$ Linear prediction scores for each class are obtained
- $s_c = w_c^\top x + b_c$
- *w_c* are class specific weights
- $\cdot b_c$ is class specific bias

ML Model	Test Accuracy (%)
BoW/SVM (V=70631 words)	80.10
CNN1 (H=1, F=600)	79.79
CNN2 (H=2, F=800)	80.19
CNN3 (H=3, F=600)	79.75

Table 3: Performance of different ML Models

BoW/SVM as Baseline

LRP Decomposition

- $R_i = (w_c)_i \cdot x_i + b_c/D$
- D is the number of non-zero entries of x

Vector Document Representation

- *d* is built component-wise
- $\forall_i : d_i = R_i \cdot \tilde{x}_i$
- Replacing R_i with a TFIDF score allows comparability

Why is this Approach the Baseline?

- Relies on word frequencies
- · All words in the embeddings are equidistant

Quality of Word References

How to compare relevance scores assigned by algorithms? Intrinsic Validation

Counting Words	Deleting Words
Creating a list of the most	Removing words and measuring
relevant words for a category	the decrease of the
across all documents	classification score

The second approach grants an objective estimation to compare relevance decomposition methods

How to compare the explanatory power of ML models? Extrinsic Validation

Problems

- Need for common evaluation basis
- Classifiers differ in their reaction to removed words

Approach

Comparing models by how 'semantic extractive' their word relevances are

How to compare the explanatory power of ML models?

Step One

Compute document summary vectors for all test set documents

Step Two

- Normalize document summary vectors to euclidean norm
- perform K-nearest neighbor classification

Step Three

- Repeat Step Two over ten random data splits
- Average KNN classification accuracies

The maximum KNN accuracy is used as explanatory power index

Results

Identification of Relevant Words

CNN2

sci.space (8.1)	Yes, expandingeness does feel like filling. It may feel strange at first, but the body does adjust. The feeling is not too different from that of sky diving. Such as the body's reaction to a strange environment. It appears to be induced perily to physical disconfort and part to mental distress. Some people are perily to physical disconfort and part to mental distress. Some people are a constrained disconfort and part to mental distress. Some people are on a rollar coaster field than others. The mental part is usually induced by a lack of clear indication of which may is up of dom, is the Bhattle is normally oriented with its cargo tay pointed towards the start mormally oriented with its cargo tay pointed towards that one numerous tests in the tory to see how to keep the number of occurances down.	sci.space (0.3)	YES, weightlesses GBEE fiel like falling. It may feel strange at first, but the body does doisn. The feeling is not too different from that of BSG diving. And what is the BEEED ischeres of a see a strange environment. It appears to be induced parity to physical disconfer in our part to mental distress. Some BBOBE are on a roller coaster fide than others. The mental part is usually induced by a lack of clear indication of which way is up of down, is the BBOBE is normally oriented with its cargo May pointed towards BBOB, so the BBOB more like or clear for of BEEGES althouses, and BBOB is a down numerication to try to see how to keep the mamber of occurances down.
	Yes, weightlessness does feel like falling. It may feel strange at first, but the body does adjust. The feeling is not too different from that of sky diving.		Yes, weightlessness does feel <u>like falling</u> . It may feel strange at first, but Inc <u>been</u> does adjust. Inc feeling <u>is</u> not too different from that if sky diving.
sci.med (4.1)	>And what is the motion <mark>Sickness</mark> >that some astronauts occasionally experience?	(9.0-)	>And what is the notion sickness >that some astronauts occasionally experience?
	It is the body's reaction to a strange environment. It appears to be induced parily to physical Biotecome and part to mental distress. Some popule are more prove to it than others, like some people are more prove to get sick on a roller coster FileM than others. The mental part is usually findered by mormally oriented with its cargo bay pointed towards Earth (or ground) is "abow" the head of the astronauts. About 5% of the astronauts experience some form of moline Statemes, and MASA has done numerous tests in space to rty to see how to keep the number of occurances down.	sci.med	It is inc. boot : reaction to a strange environment. It appears is be indicated partly its physical Bisconfers, and part is entral distress. Some procle are more proce to it than others, like some pools are more proce to get Size an a foller coart field than others. If mental and the size is an advised by morally oriented with its carpo hay pointed towers and a strange and the size of the operance some form is outlon size as a distribution of the size of the automate is a size of the size of the size of the size of the size of the operance some form is outlon size and Mask has done numerous tests in maker to try to see how is keep in under in occurance some.

SVM

Figure 3: LRP heatmaps, positive is red, negative is blue

Identification of Relevant Words

sci.med

sci.space

comp.graphics

symptoms (7.3), treatments (6.6), med-
ication (6.4), osteopathy (6.3), ulcers
(6.2), sciatica (6.0), hypertension (6.0),
herb (5.6), doctor (5.4), physician (5.1),
Therapy (5.1), antibiotics (5.1), Asthma
(5.0), renal (5.0), medicines (4.9), caf-
feine (4.9), infection (4.9), gastrointesti-
nal (4.8), therapy (4.8), homeopathic
(4.7), medicine (4.7), allergic (4.7),
dosages (4.7), esophagitis (4.7), inflam-
mation (4.6), arrhythmias (4.6), cancer
(4.6), disease (4.6), migraine (4.6), pa-
tients (4.5).

spaceraft (11.0), orbit (10.8), NASA (8.6), Mars (7.8), moon (7.1), orbiting (7.1), Martian (6.8), orbital (6.8), shutthe (6.7), SMOS (6.6), telescope (6.5), Space (6.5), rocket (6.3), GRBs (6.0), Earth (6.0), astronaut (5.9), Moon (5.7), Shuttle (5.7), lander (5.6), Flyby (5.3), planets (5.2), Hubble (5.2), Soyuz (5.2), geosynchronous (5.2), Endeavour (5.1), space (5.0), planetary (4.9), Nasa (4.9), Astronomy (4.9), astronaut (4.9). Graphics (6.9), raytracing (6.8), graphics (6.8), polygon (6.5), animation (6.3), Image (6.2), shaders (6.2), pixel (5.7), fractal (5.5), <u>rewports</u> (5.5), Autodesk (5.4), visualization (5.2), RGB (5.1), images (5.0), TIFF (5.0), Corel (4.9), Studio (4.9), algorithm (4.8), Bezier (4.8), polygons (4.7), GIF (4.7), Pixel (4.6), algorithms (4.5), medo (4.5), image (4.4), radiosity (4.4), <u>AutoDesk</u> (4.3), Studios (4.3), HFGL (4.2), DEG (4.2).

Figure 4: The 30 most relevant words for CNN2

sci.med

cancer (1.4), photography (1.0), doctor (1.0), msg (0.9), disease (0.9), medical (0.8), sleep (0.8), radiologist (0.7), eye (0.7), treatment (0.7), prozac (0.7), vitamin (0.7), spilepsy (0.7), health (0.6), yeast (0.6), skin (0.6), pain (0.5), health (0.6), (0.5), physical (0.5), she (0.5), needles (0.5), dn (0.5), circumcision (0.5), syndrome (0.5), migraine (0.5), antibiotic (0.5), water (0.5), blodo (0.5), fat (0.4), weight (0.4).

sci.space

space (1.6), launch (1.4), ics.uci.edu (1.2), mooi (1.1), orbit (1.0), mars (1.0), pat (1.0), nasa (0.9), dietz (0.9), shuttie (0.8), solar (0.7), command (0.7), henry (0.6), fred (0.6), gamma (0.6), sci.space (0.6), pluto (0.6), satellite (0.6), dex (0.6), nicho (0.6), satellite (0.6), dex (0.6), nicho (0.6), sateronory (0.5), lunar (0.5), poro (0.5), hag (0.5), sky (0.5), spacecarfa (0.5), gravity (0.5), scicom.alphacdc.com (0.5), nick (0.4), roland (0.4).

comp.graphics

graphics (2.0), phigs (1.4), image (1.4), images (1.4), xv (1.3), tiff (1.2), polygons (1.1), comp.graphics (1.0), mpeg (1.0), format (1.0), siggraph (1.0), povray (0.9), quicktime (0.8), bockamp (0.8), surface (0.8), animation (0.8), iges (0.8), studio (0.8), jpeg (0.8), pov (0.7), dec (0.7), scodal (0.7), algorithm (0.7), genoa (0.7), sgi (0.7), palette (0.6), vga (0.6), impulse (0.6), c (0.6), rgb (0.6).

Document Summary Vectors



Figure 6: The 30 most relevant words for Bow/SVM

How good is LRP in identifying relevant words?

- Delete Sequence of words from document
- Classify document again
- Report as function of accuracy and number of missing words

Three different approaches

- 1. Start with correctly classified documents
 - Delete words in decreasing order of their relevance
- 2. Start with falsely classified documents
 - Delete words in increasing order of their relevance
- 3. Start with falsely classified documents
 - Delete words in decreasing order of their score

Evaluating LRP



Figure 7: Word deletion experiments

Quantifying Explanatory Power

Semantic Extraction		Explanatory Power Index (EPI)	KNN parameter
word2vec/CNN1	LRP (ew)	0.8045 (± 0.0044)	K = 10
	SA (ew)	0.7924 (± 0.0052)	K = 9
	LRP	0.7792 (± 0.0047)	K = 8
	SA	0.7773 (± 0.0041)	K = 6
word2vec/CNN2	LRP (ew)	0.8076 (± 0.0041)	K = 10
	SA (ew)	0.7993 (± 0.0045)	K = 9
	LRP	0.7847 (± 0.0043)	K = 8
	SA	0.7767 (± 0.0053)	K = 8
word2vec/CNN3	LRP (ew)	0.8034 (± 0.0039)	K = 13
	SA (ew)	0.7931 (± 0.0048)	K = 10
	LRP	0.7793 (± 0.0037)	K = 7
	SA	0.7739 (± 0.0054)	K = 6
word2vec	TFIDF	0.6816 (± 0.0044)	K = 1
	uniform	0.6208 (± 0.0052)	K = 1
BoW/SVM	LRP	0.7978 (± 0.0048)	K = 14
	SA	0.7837 (± 0.0047)	K = 17
BoW	TFIDF	0.7592 (± 0.0039)	K = 1
	uniform	0.6669 (± 0.0061)	K = 1

Table 4: Results over 10 random data splits

Quantifying Explanatory Power



Figure 8: Word deletion experiments

Questions?