BoW Models

Vsevolod Dyomkin

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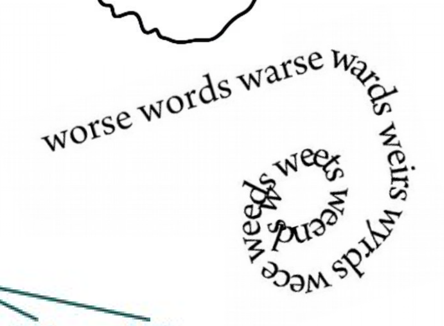
NLP Viewpoints

bag-of-words

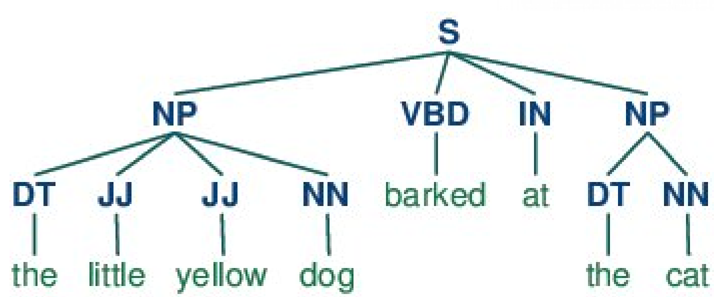
lexics

sequence



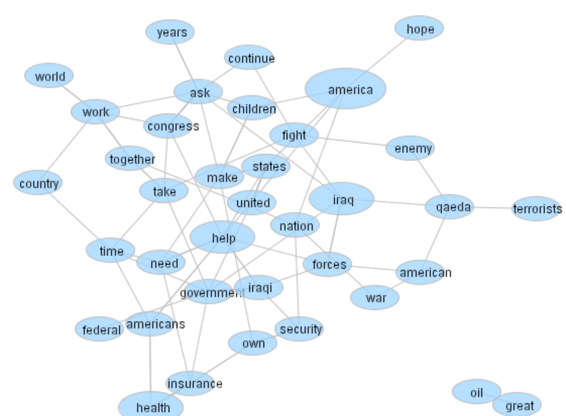
???

tree



syntax

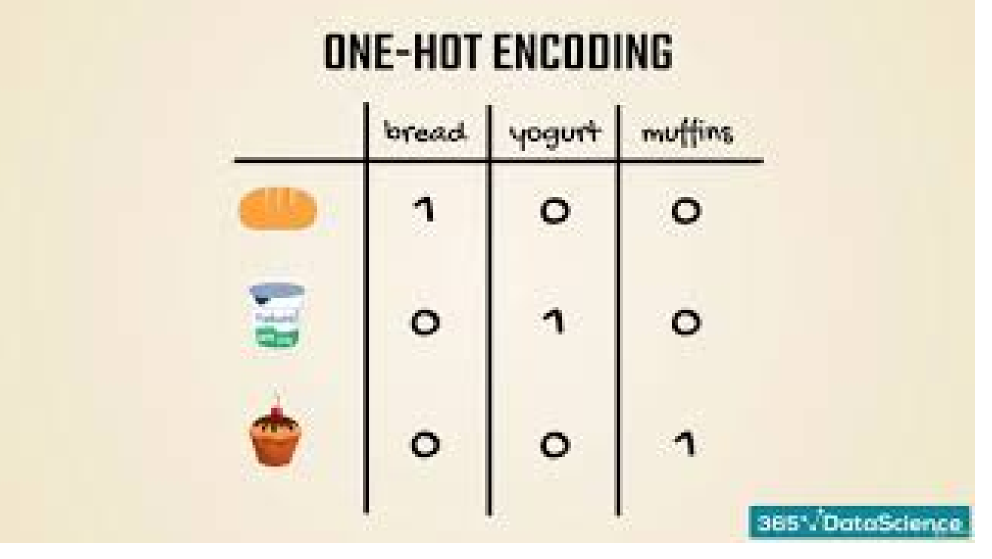
graph



semantics

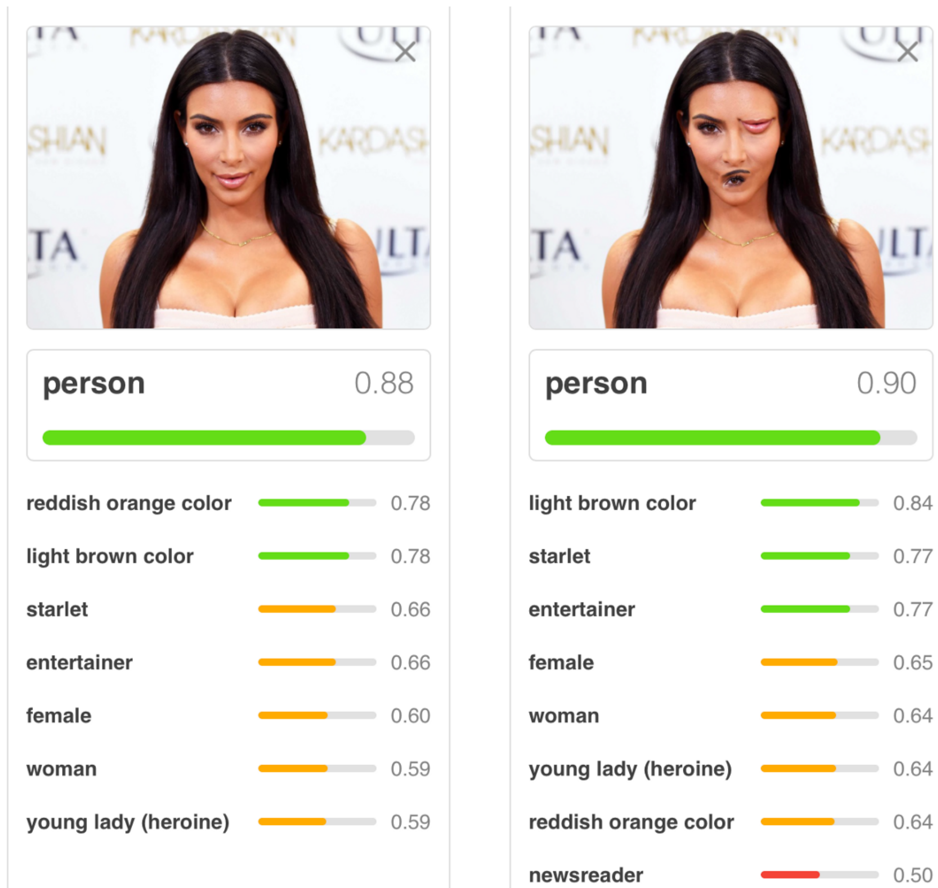
The Glorious BoW

* Simplest model
* Feature vector in N-dim space - vector of words (with counts) (N = dictionary size) - a.k.a **1-hot representation**



* Position information disregarded
* Works mostly for c12n

… not only for text



https://hackernoon.com/capsule-networks-are-shaking-up-ai-heres-how-to-use-them-c233a0971952

Spam Identification

A 2-class whole text classification problem with a bias towards minimizing FPs.

Default approach - Rule-based (SpamAssassin)

Apache SpamAssassin

Problems:
- scales poorly
- hard to reach arbitrary precision
- hard to rank the importance of complex features
- hard to interpret score and use it in upstream calculations

“A Plan for Spam”

Proposed by Paul Graham
(http://www.paulgraham.com/spam.html)

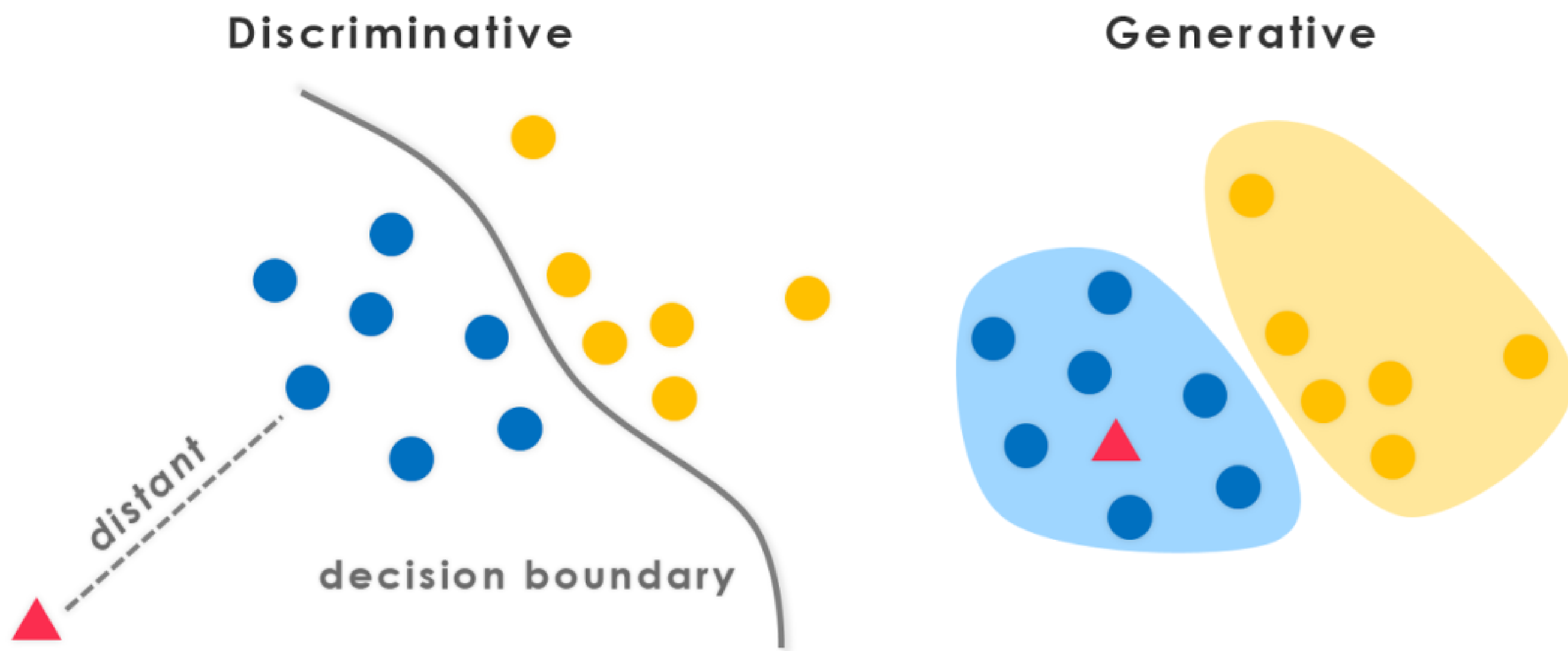
1. Use the BoW model
2. Use the Naive Bayes learning algorithm
3. Train on a balanced corpus

Initial results: Rec: 92%, Prec: 98.84%
Improved results: Rec: 99.5%, Prec: 99.97%

Generative Models

* Model joint probability of a sample and label:
  can be used both to classify
  and generate
* Introduce some structure (constraints)
* That’s why accuracy is usually asymptotically lower (but learn faster)
* Examples:
  - Naive Bayes
  - GMM
  - HMM
  - PCFG
  - GAN

Generative vs Discriminative Models

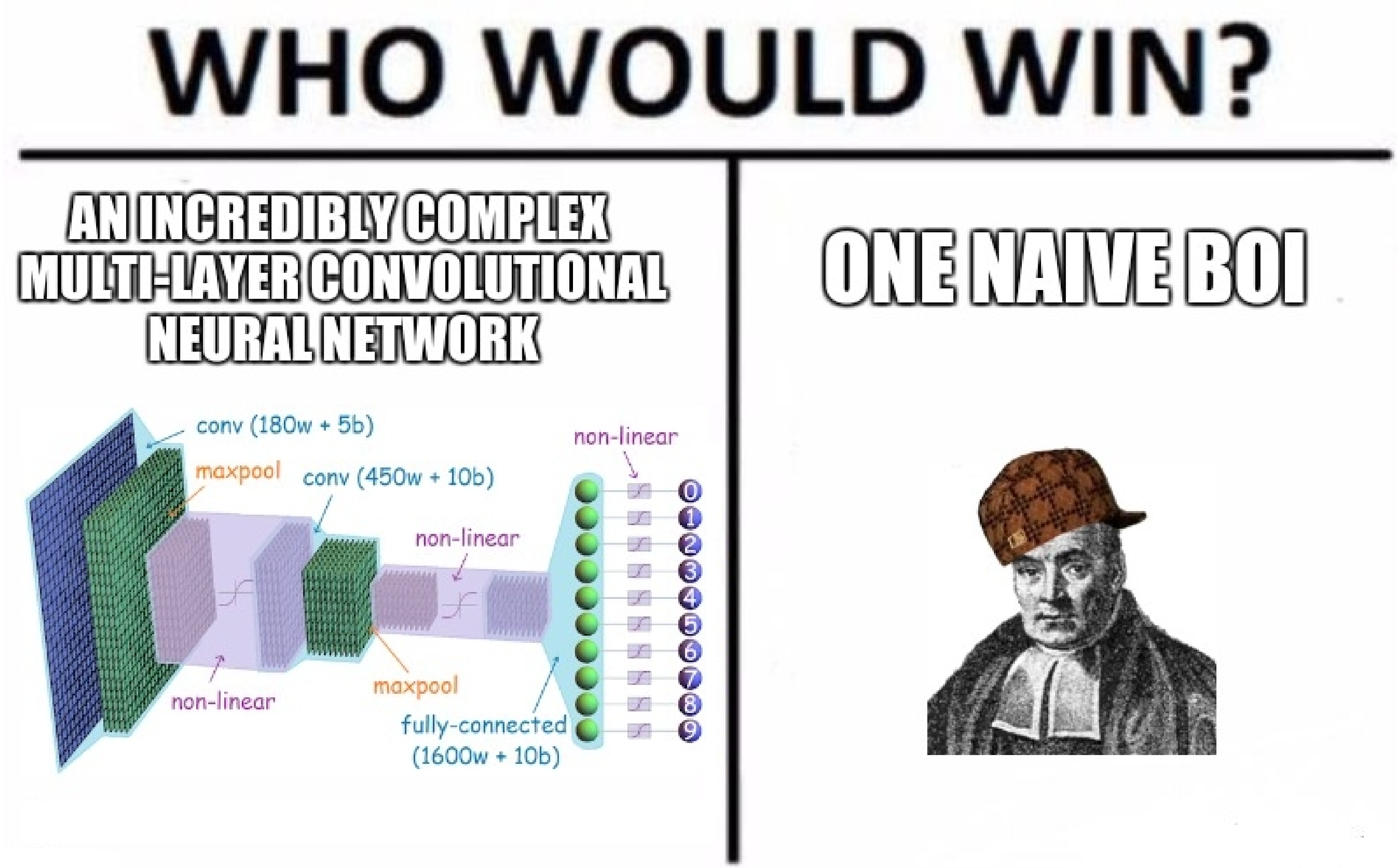


Generative vs Discriminative Models

https://stats.stackexchange.com/questions/12421/generative-vs-discriminative

a) The generative model does indeed have a higher asymptotic error (as the number of training examples become large) than the discriminative model but
b) The generative model may also approach its asymptotic error much faster than the discriminative model — possibly with a number of training examples that is only logarithmic, rather than linear, in the number of parameters
http://ai.stanford.edu/~ang/papers/nips01-discriminativegenerative.pdf

Naive Bayes Classifier



Naive Bayes Classifier

P(Y|X) = P(Y) * P(X|Y) / P(X)
select Y = argmax P(Y|x)

Naive step:

```
    P(Y|x) = P(Y) * prod(P(x|Y))
                    for all x in X
```

(P(x) is marginalized out because it's the same for all Y)

NB Model for Spam

$$P(spam|penis, viagra)$$

$$= \frac{P(penis|spam) * P(viagra|spam) * P(spam)}{P(penis) * P(viagra)}$$

$$= \frac{\frac{24}{30} * \frac{20}{30} * \frac{30}{74}}{\frac{25}{74} * \frac{51}{74}} = 0.928$$

https://alexn.org/blog/2012/02/09/howto-build-naive-bayes-classifier.html

The Value of Pre/Post-Processing

“Clever tricks”:
- title is more important than text
- text in the beginning is more important than at the end
- UNKs handling (spammers are smart)

Pre-processing:
- numbers pre-processing
- take only 15 most “interesting” words

…also: non-NLP features

NB Model for LangID

* The problem of using words
* Character ngrams to the rescue
* Combining them

Discriminative Models

* Model conditional probability of label, given a sample:
  can be used only to classify
* Training is direct
* Examples:
  - kNN
  - Perceptron & Averaged Perceptron
  - Logistic Regression (aka MaxEnt)
  - AROW
  - SVM
  - CRF
  - Feed-forward Neural Nets

(Averaged) Perceptron

* Simplest linear discriminative model
* On-line learning
* When averaged — ensemble, assimptotic optimality

Perceptron learning rule:

```
def train(self, nr_iter, examples):
    for i in range(nr_iter):
        for features, true_tag in examples:
            guess = self.predict(features)
            if guess != true_tag:
                for f in features:
                    self.weights[f][true_tag] += 1
                    self.weights[f][guess] -= 1
        random.shuffle(examples)
```

https://explosion.ai/blog/part-of-speech-pos-tagger-in-python

Sentiment Analysis

A 3-class whole-text[1] classification problem.

Default approach - Lexicon-based

Possible problems:
- ???

BoW Models for Sentiment

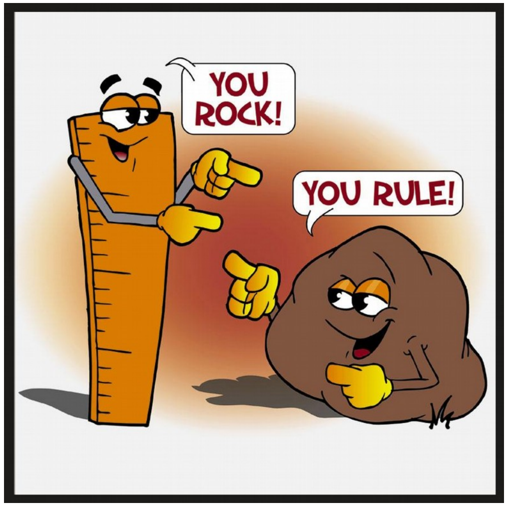
Features: words, bigrams

Models:
* Multinomial NB
* SVM with 2nd-order polynomial kernel
* NBSVM

https://www.aclweb.org/anthology/P12-2018

BoW Fail Cases

* polysemy
* negation
* neutralization
* multiple sentiments
* multiple objects
* ambiguity
* noise (errors)



Negation Examples

* Morphological:
  The food was no good.
  I did not like them.
  Their food was without any taste.
  They lack good manners.
* Syntactic:
  If only their prices weren't that high!
  I wish the food they served was more delicious.
  Unlike The X, The Y has great service.
  If they weren't rude, they wouldn't have lost their customers.
  They are unlikely to improve.

False Negation

High prices were no surprise.

There is no reason to not like them.

It will bring us nowhere, but to success.

There’s no doubt they are going to win the market.

The restaurant was not only cozy, but also located in a wonderful place.

Not only were the waiters rude, but they also brought the wrong dishes.

Neutralization

* Morphological:

  The X was once described as a leader in sales.

  Earlier, The X used to put off the customers a lot.

* Syntactic:

  If they engage more customers, they will earn more.

  All the hotels, excluding The X Hotel, were sued.

  The restaurant was neither good, nor bad.

Multiple Sentiments

My sons loved The Playground. They are great, not like The Sandbox with their unsanitary kitchen. High prices were no surprise, though.

Ambiguity

The company is worth the words that were said earlier.

It tastes like beer.

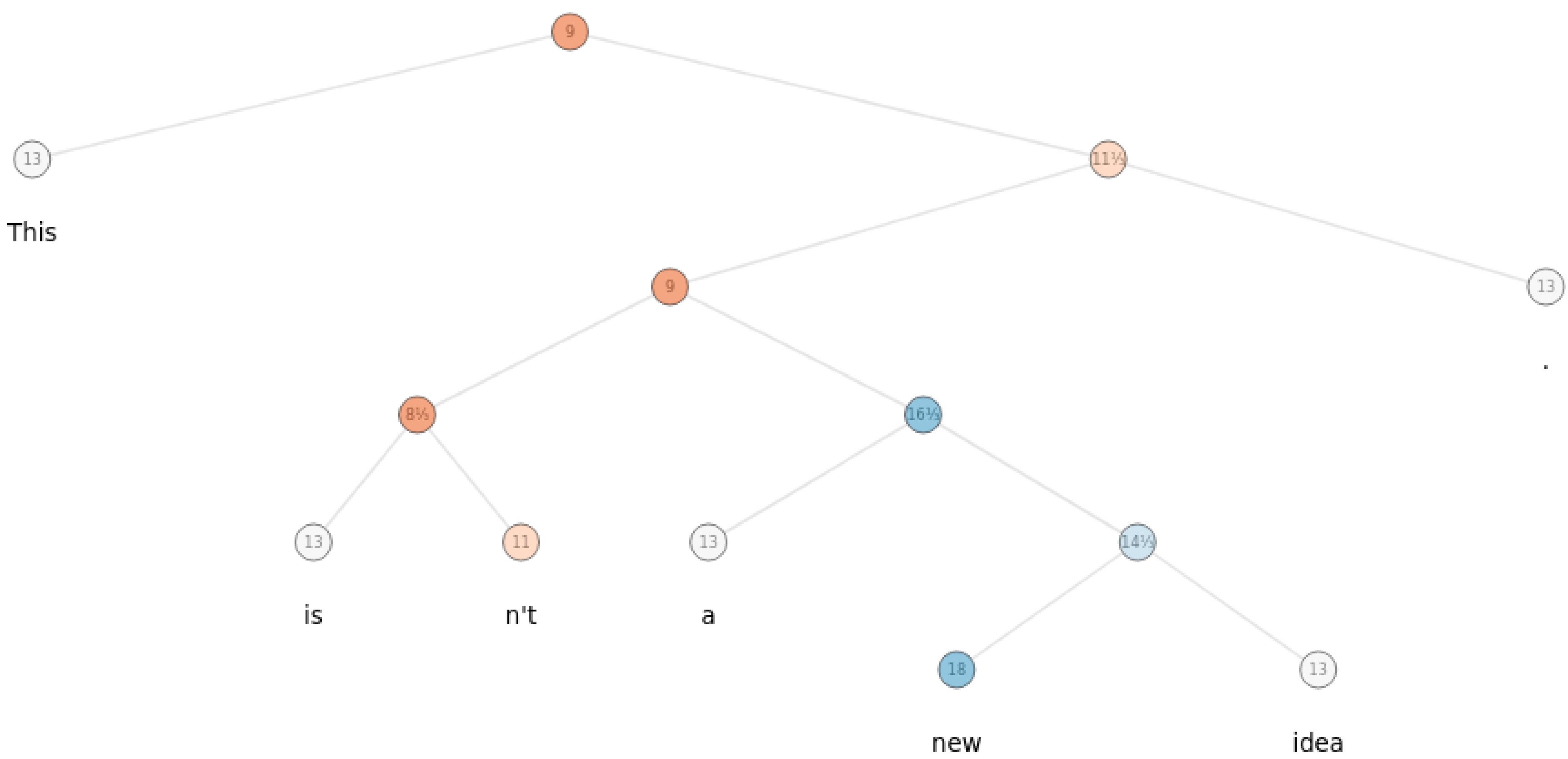
It’s in the same league with The Happiness Project, trust me.

Obama was right about it.

More BoW “Tricks”

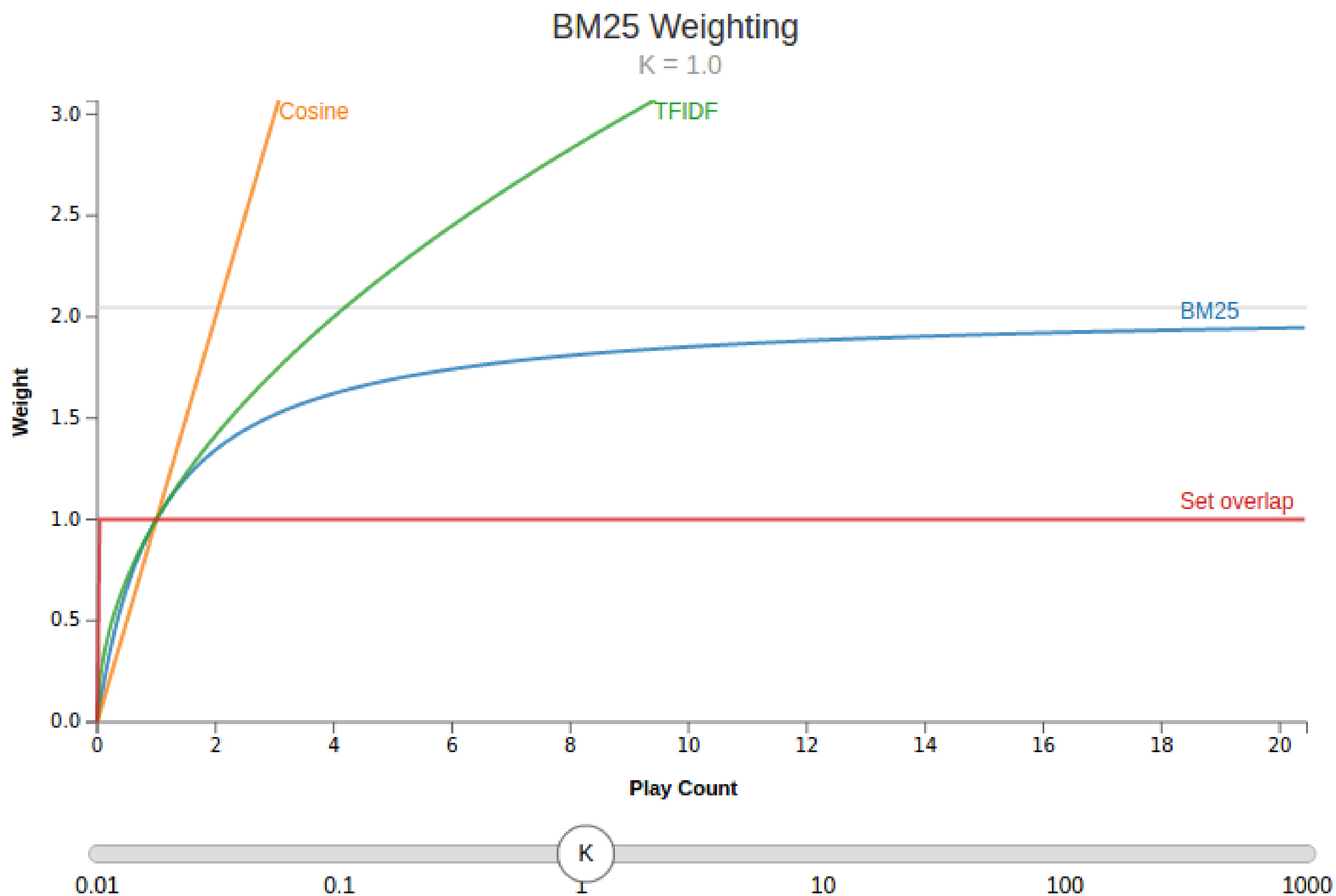
* normalization of special tokens
* lemmatization/stemming
* stopwords removal
* filtering by “relevance” (e.g. TF-IDF)
* filtering by LM, parse, SRL…
* combining words (negation, prepostions, NER…)

Sentiment Treebank



https://nlp.stanford.edu/sentiment/treebank.html

Similarity Metrics



http://www.benfrederickson.com/distance-metrics/

TF-IDF

A classic IR technic for ranking relevancy

Variants of term frequency (TF) weight

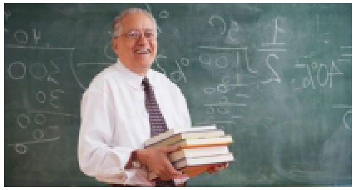
weighting scheme	TF weight
binary	$0, 1$
raw count	$f_{t,d}$
term frequency	$f_{t,d} \Big/ \sum_{t' \in d} f_{t',d}$
log normalization	$1 + \log(f_{t,d})$
double normalization 0.5	$0.5 + 0.5 \cdot \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$
double normalization K	$K + (1 - K) \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$

TF-IDF

Variants of inverse document frequency (IDF) weight

weighting scheme	IDF weight ($n_t = \|\{d \in D : t \in d\}\|$)
unary	1
inverse document frequency	$\log \frac{N}{n_t} = -\log \frac{n_t}{N}$
inverse document frequency smooth	$\log\left(1 + \frac{N}{n_t}\right)$
inverse document frequency max	$\log\left(\frac{\max_{\{t' \in d\}} n_{t'}}{1 + n_t}\right)$
probabilistic inverse document frequency	$\log \frac{N - n_t}{n_t}$

Science Pulse

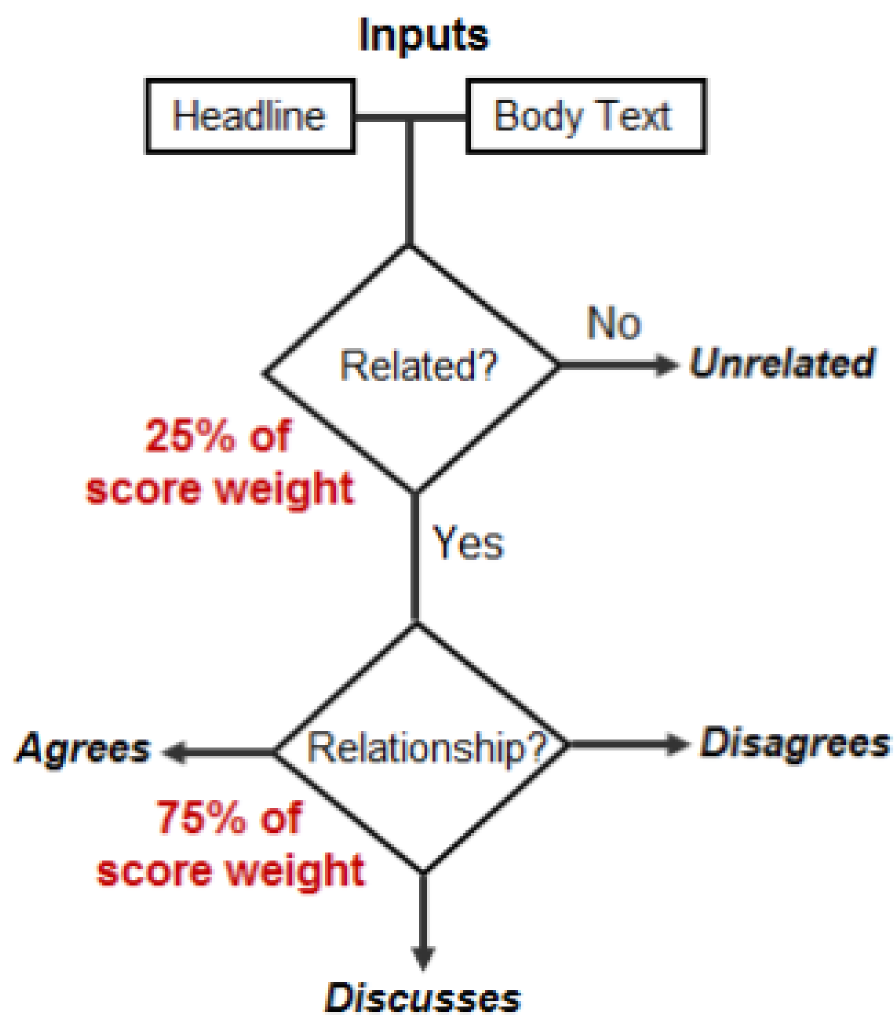


Keyphrase	Weight	Keyphrase	Weight
massive multiple input output	7,25	все буде добре	1
long short term memory architecture	5,12	коли тебе нема	1
Live action virtual reality games	3,15	небо над дніпром	1
low rank hankel matrix completion	3,04	хочу напитись тобою	0,78
multi point wireless energy transmission	3,01	жити без мети	0,78
tree augmented naive bayes classifier	2,89	мила моя сьюзі	0,78
long short term memorized fusion	2,15	тінь твого тіла	0,75
fine grained entity type classification	1,51	коли настане день	0,75
high speed railway communication systems	1,27	кожну хвилину життя	0,75
partially observable markov decision process	1,13	коли тобі важко	0,75

https://aiukraine.com/wp-content/uploads/2016/09/Tetiana-Kodliuk.pdf

Stance Detection

A 4-class whole text Hierarchical classification problem:
* unrelated,
* related:
  - discuss
  - agree
  - disagree



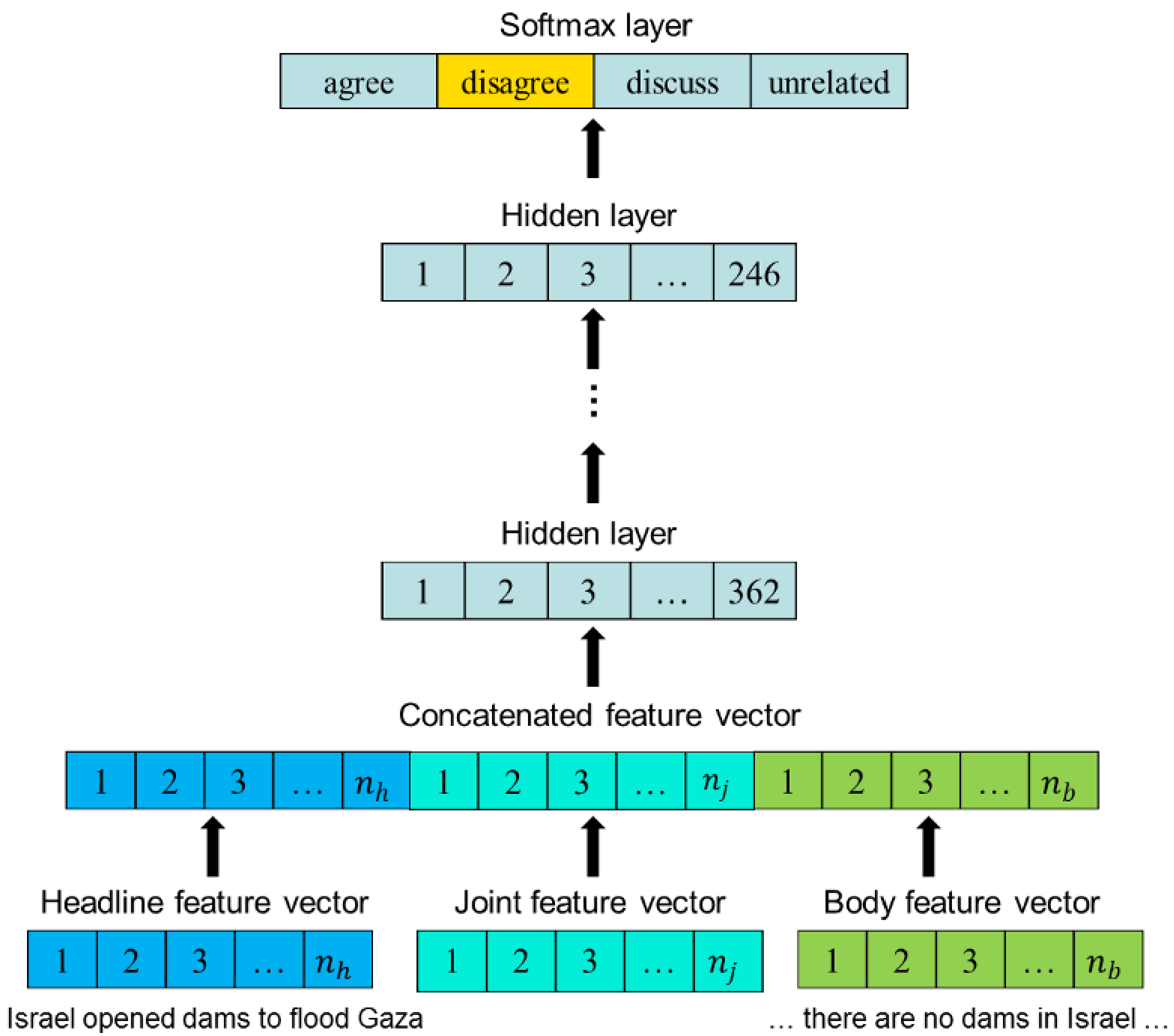
https://github.com/FakeNewsChallenge/fnc-1

TF-IDF Cosine Similarity Baseline

	agree	disagree	discuss	unrelated
agree	94	14	111	543
disagree	13	27	9	113
discuss	11	31	607	1151
unrelated	379	91	650	5778

Score: 2219.75 out of 4448.5   (49.898842306395416%)

BoW-MLP Model



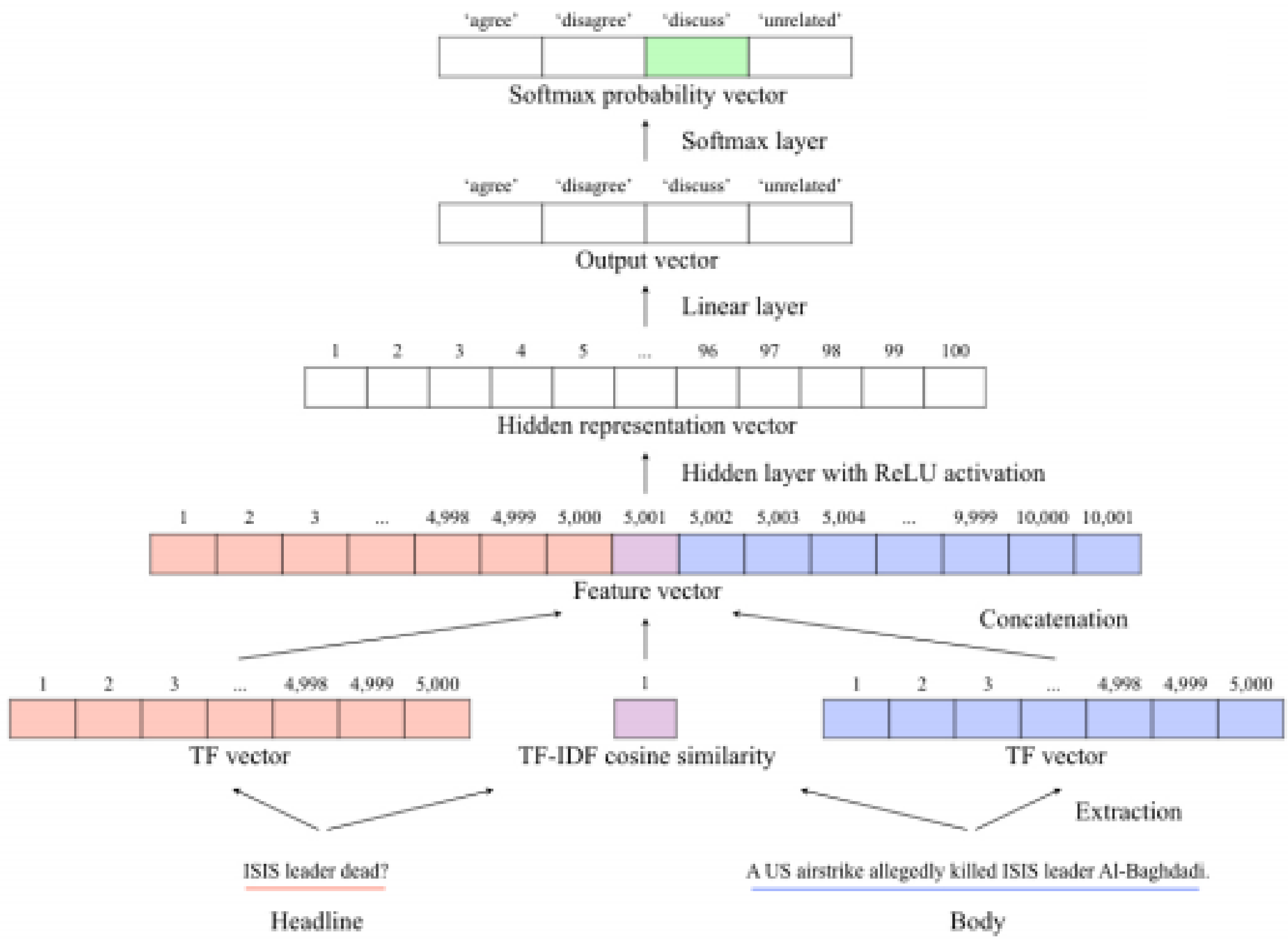
https://medium.com/@andre134679/team-athene-on-the-fake-news-challenge-28a5cf5e017b

BoW-MLP Model

Features:
* Words
* Non-Negative Matrix Factorization
* Latent Semantic Indexing
* Latent Semantic Analysis
* PPDB

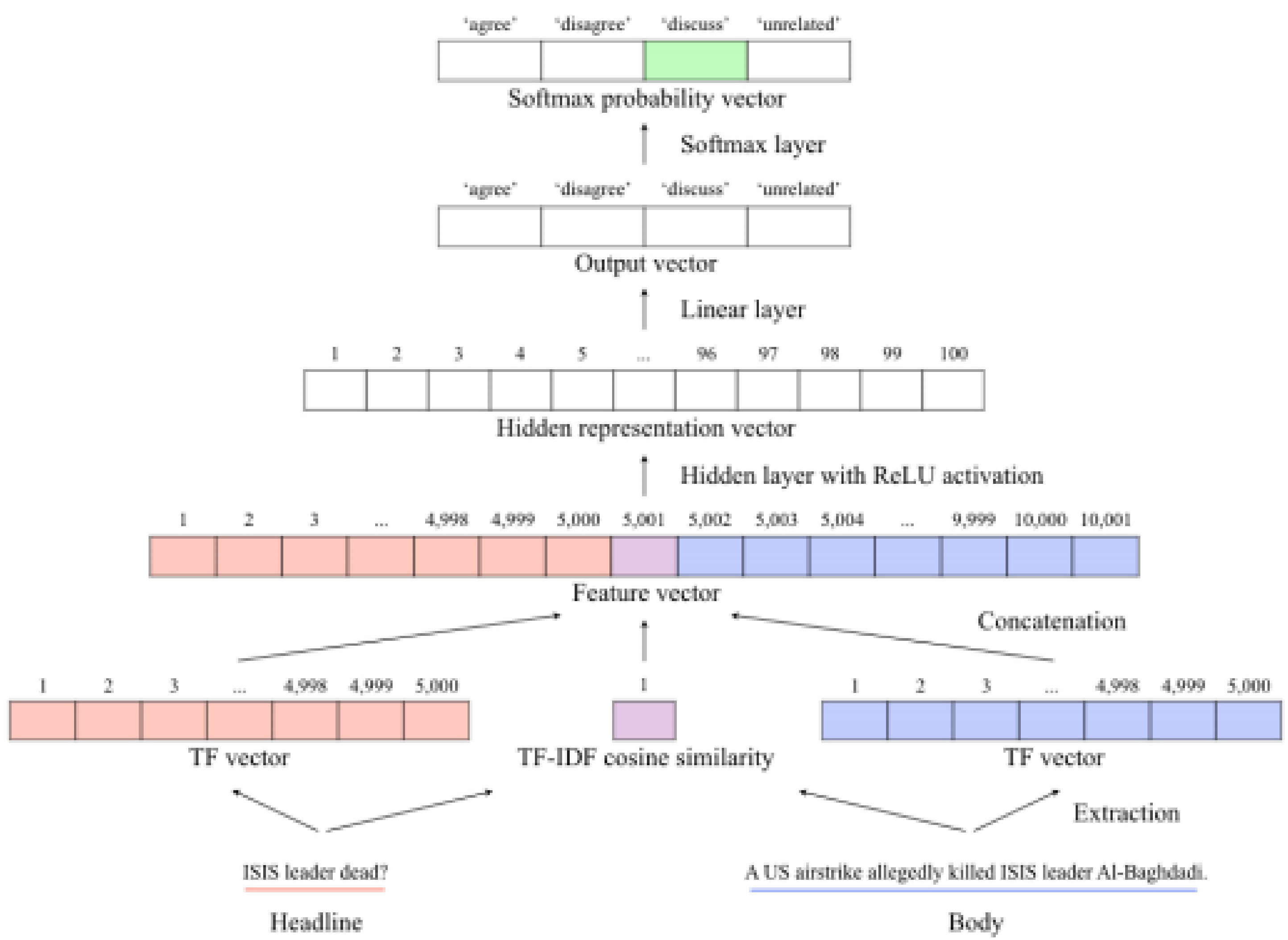
	Agree	Disagree	Discuss	Unrelated	Accuracy (%)
Agree	851	69	826	157	44.72
Disagree	241	66	241	149	9.47
Discuss	466	37	3611	350	80.89
Unrelated	19	4	115	18211	99.25
Overall					89.5

Simpler BoW-MLP Model



https://128.84.21.199/pdf/1707.03264.pdf

Simpler BoW-MLP Model



https://128.84.21.199/pdf/1707.03264.pdf

BoW Recap

Pros:
+ simple
+ easy to compute
+ flexible
+ doesn't require lots of data
+ with lots of data works very well

Cons:
- doesn't capture order
- hard to capture inter-word relations
- hard to scale to real-world vocabularies
- poor generalization

Read More

BoW in CV:

- http://cs.nyu.edu/~fergus/teaching/vision_2012/9_BoW.pdf

Sentiment analysis:

- http://www.datasciencecentral.com/profiles/blogs/test?xg_source=activity
- http://ataspinar.com/2015/11/16/text-classification-and-sentiment-analysis/
- http://ataspinar.com/2016/02/15/sentiment-analysis-with-the-naive-bayes-classifier/
- https://www.cs.uic.edu/~liub/FBS/Sentiment-Analysis-tutorial-AAAI-2011.pdf

Bonus:

- https://nlpers.blogspot.com/2014/11/the-myth-of-strong-baseline.html