A Word-Complexity Lexicon and **A Neural Readability Ranking Model** for Lexical Simplification

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INPUT: *Applesauce is a **puree** made of apples.*

OUTPUT: *Applesauce is a **soft paste**. It is made of apples.*

Text Simplification

INPUT: *Applesauce is a* ***<u>puree</u>*** *made of apples.*

OUTPUT: *Applesauce is a* ***<u>soft paste</u>***. *It is made of apples.*

Applications

- Reading assistance for children, non-native speakers and disabled.
- Improve other NLP tasks (MT, summarization …)

Assessing **word complexity** is vital!

INPUT: *Applesauce is a puree made of apples.*

OUTPUT: *Applesauce is a soft paste. It is made of apples.*

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Complex Word Identification

Assessing **word complexity** is vital!

INPUT: *Applesauce is a* ***puree*** *made of apples.*

OUTPUT: *Applesauce is a* ***soft paste.*** *It is made of apples.*

liquidized sauce

thick liquid

Complex Word Identification - Substitution Generation

Assessing **word complexity** is vital!

INPUT: *Applesauce is a* ***puree*** *made of apples.*

OUTPUT: *Applesauce is a* ***soft paste****. It is made of apples.*

thick liquid

liquidized sauce

complex

Complex Word Identification - Substitution Generation - Substitution Ranking

A Large Word-complexity Lexicon

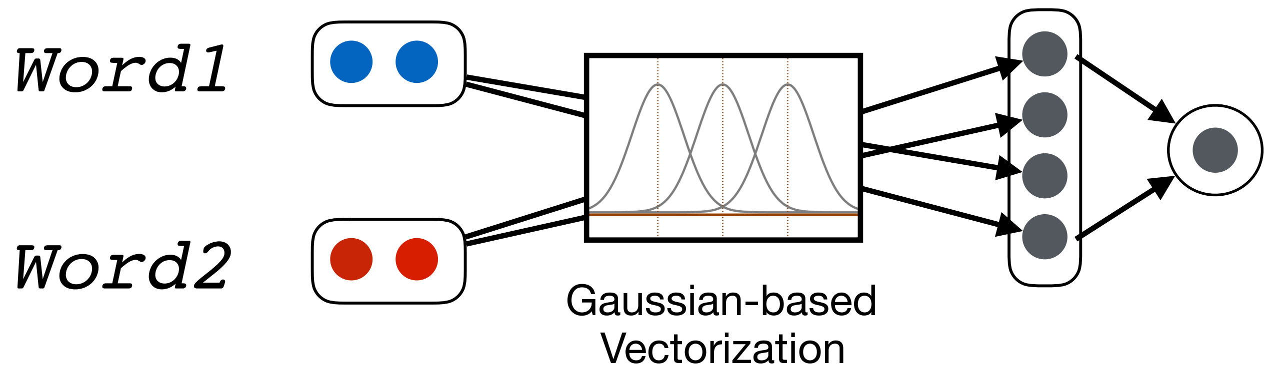
- 15,000 English words w/ human ratings

day	1.0
convenient	2.4
transmitted	3.2
cohort	4.3
assay	5.8

MIN 1 (simple)

MAX 6 (complex)

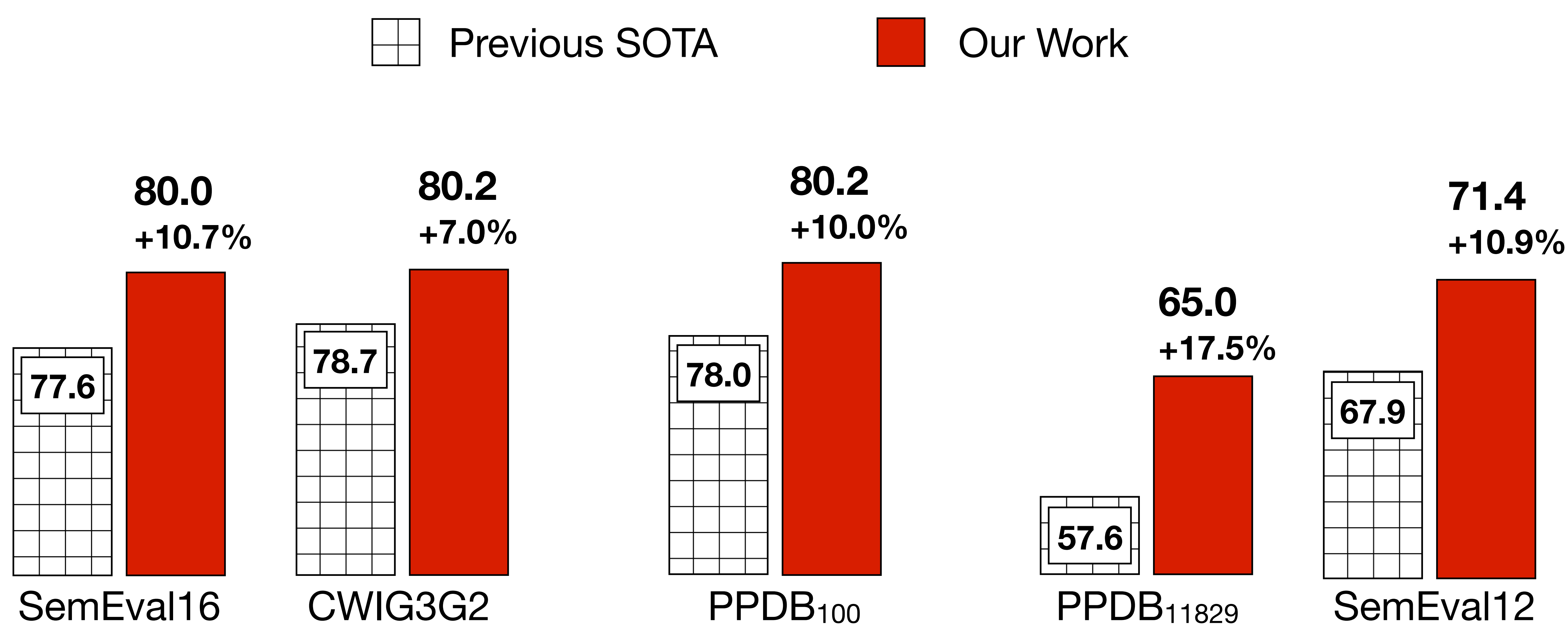
- predict relative complexity for any given words or phrases



P(*Word1* > *Word2*) = 0.91

A Pairwise Neural Ranking Model

- improve the state-of-the-art significantly for all lexical simplification tasks



Complex Word Identification - Substitution Generation - Substitution Ranking

% is relative error reduction

Previous Work

Rely on **heuristics and corpus level features** to measure word complexity

- Word length

  (Shardlow 2013, Biran et. al. 2011, and many others)

- Word frequency in corpus

  (Bott et. al. 2011, Kajiwara et. al. 2013, Horn et. al. 2014, and many others)

- Language model probability

  (Glavas & Stajner 2015, Paetzold & Special 2016/17, and many others)

Weakness of Previous Work

Assumption #1: shorter words are simpler → **Wrong! (21% of time*)**

duly > *thoroughly*

pundit > *professional*

alien > *stranger*

* based on 2272 lexical paraphrases sampled from PPDB

Weakness of Previous Work

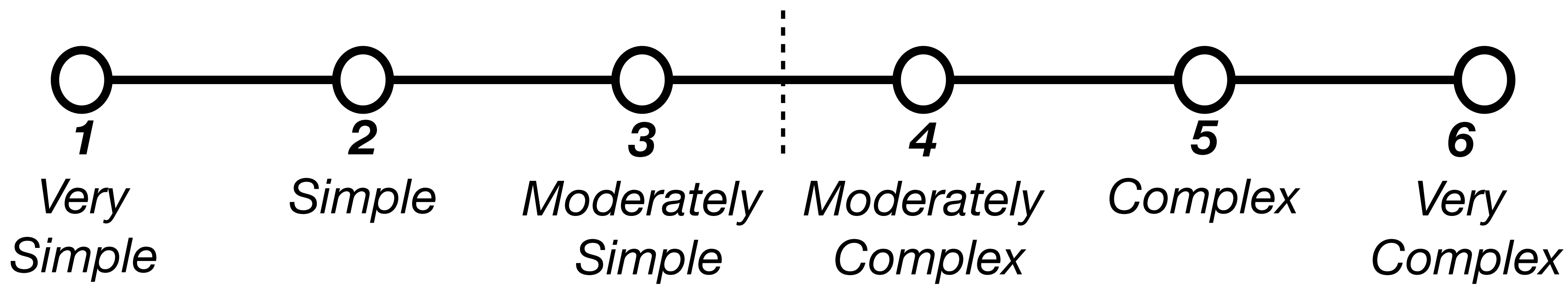
Assumption #2: more frequent words are simpler → **Wrong! (14% of time*)**

folly	>	*foolishness*
scheme	>	*outline*
distress	>	*discomfort*

* based on 2272 lexical paraphrases sampled from PPDB

A Large Word-complexity Lexicon

- 15,000 most frequent English words from Google 1T ngram corpus
- Rated on a 6-point Likert scale



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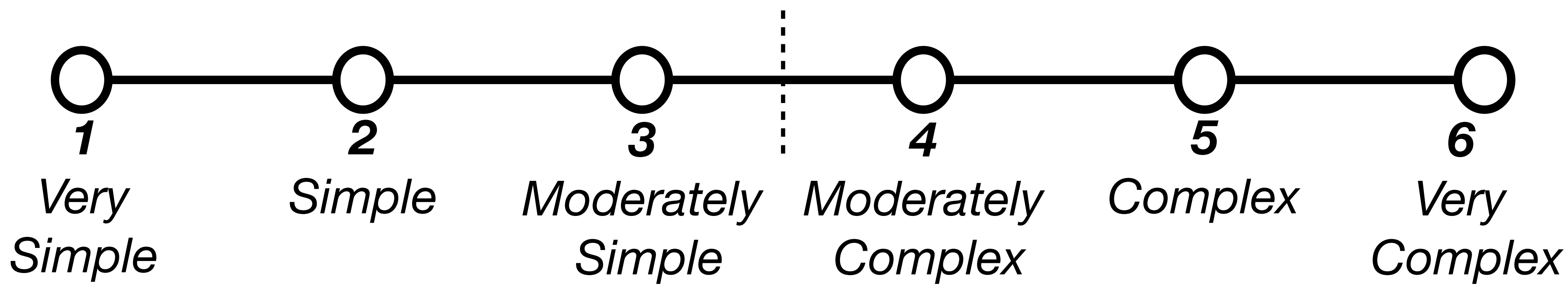
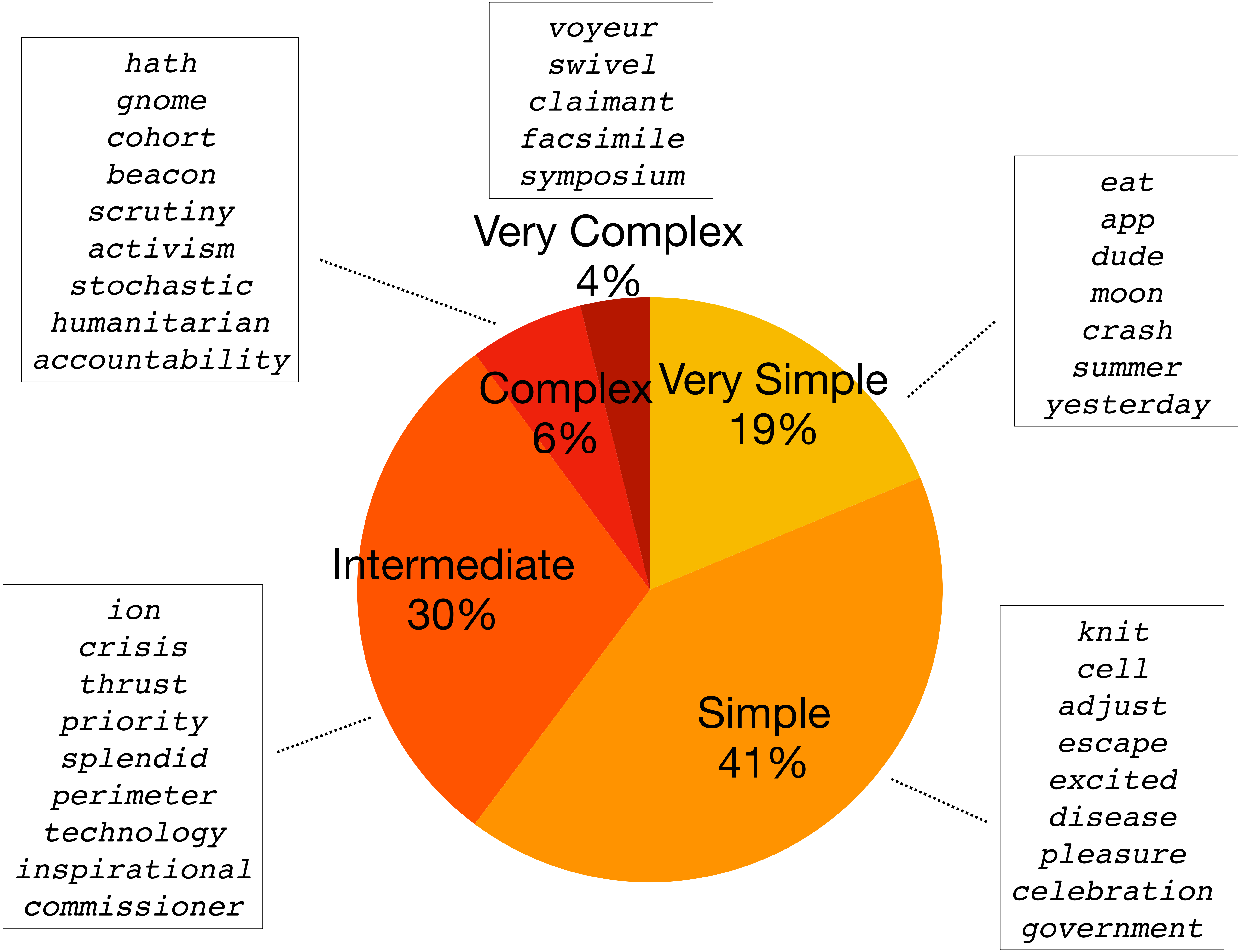


- 11 annotators (non-native speakers)
- 5 ~ 7 ratings for each word
- 2.5 hours to rate 1000 words

Quick n' Easy

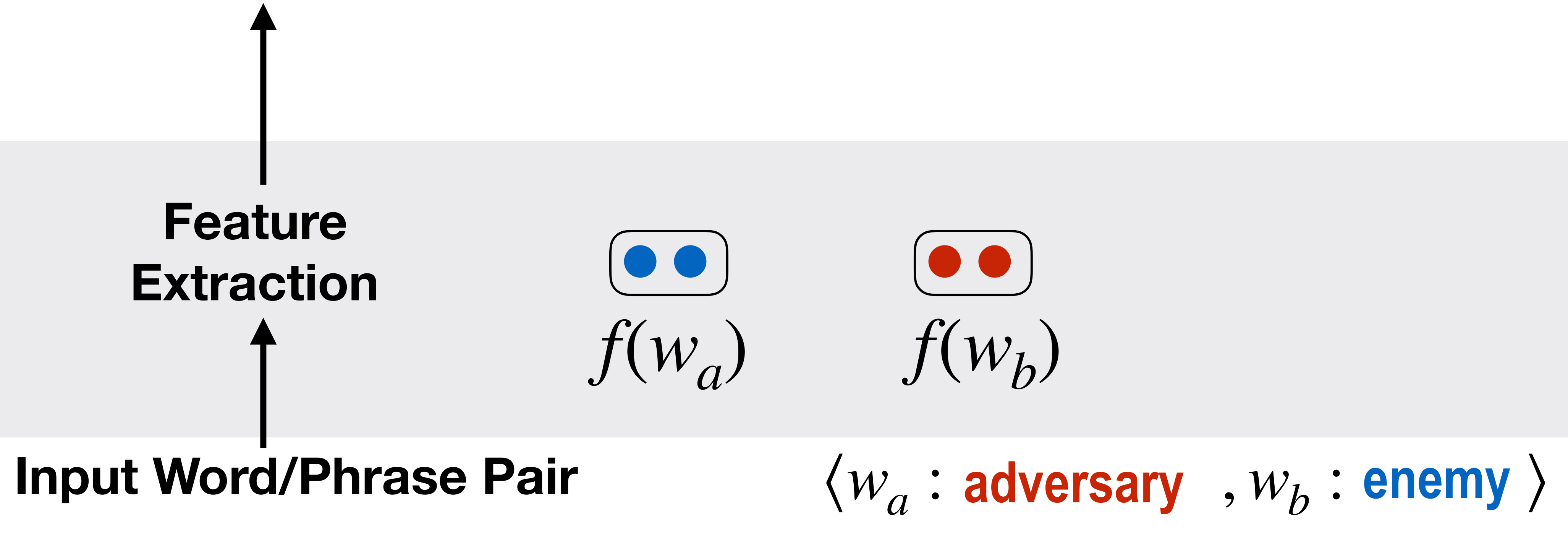

hath
gnome
cohort
beacon
scrutiny
activism
stochastic
humanitarian
accountability
voyeur
swivel
claimant
facsimile
symposium
Very Complex
4%
eat
app
dude
moon
crash
summer
yesterday
Complex
6%
Very Simple
19%
Intermediate
30%
ion
crisis
thrust
priority
splendid
perimeter
technology
inspirational
commissioner
Simple
41%
knit
cell
adjust
escape
excited
disease
pleasure
celebration
government

- Inter-annotator agreement is 0.64 (Pearson correlation)
- One annotator rating vs. mean of the rest

Word	Score	A1	A2	A3	A4	A5
`muscles`	1.6	2	1	2	2	1
`pattern`	2.4	2	3	1	1	3
`educational`	3.2	3	3	3	3	4
`cortex`	4.2	4	4	4	4	5
`assay`	5.8	6	6	6	5	6

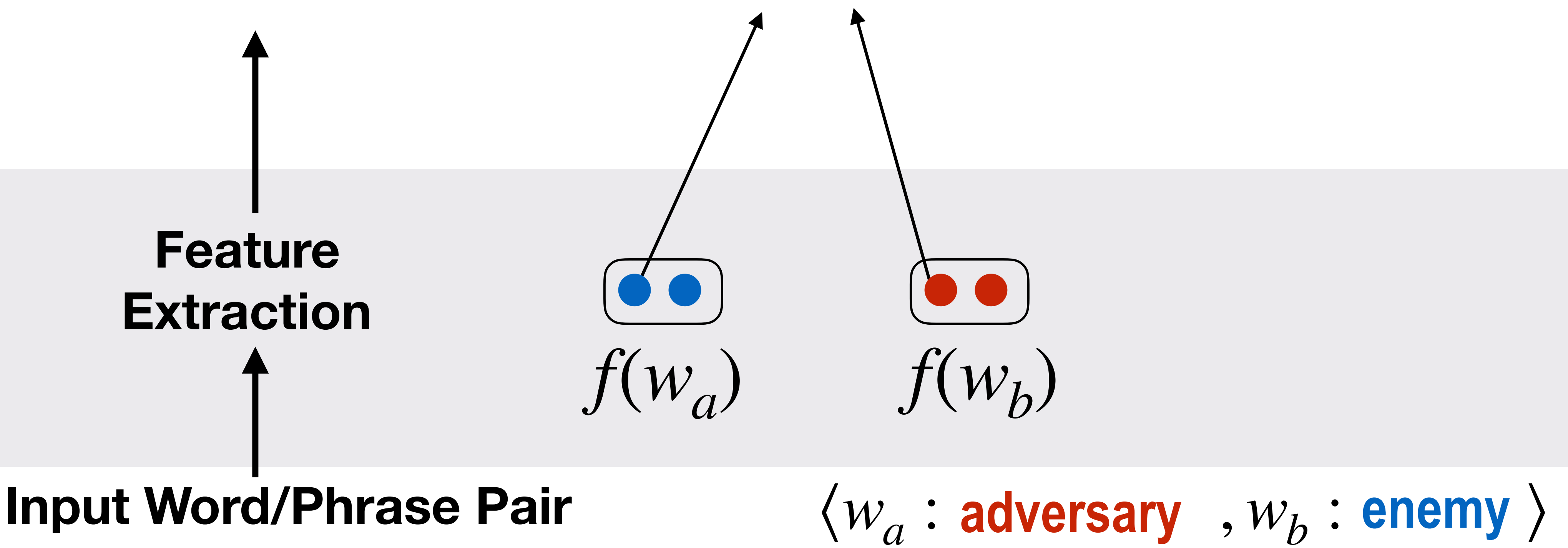
difference (one vs. rest)	< **0.5** for **47%** of annotations
	< **1.0** for **78%** of annotations
	< **1.5** for **93%** of annotations

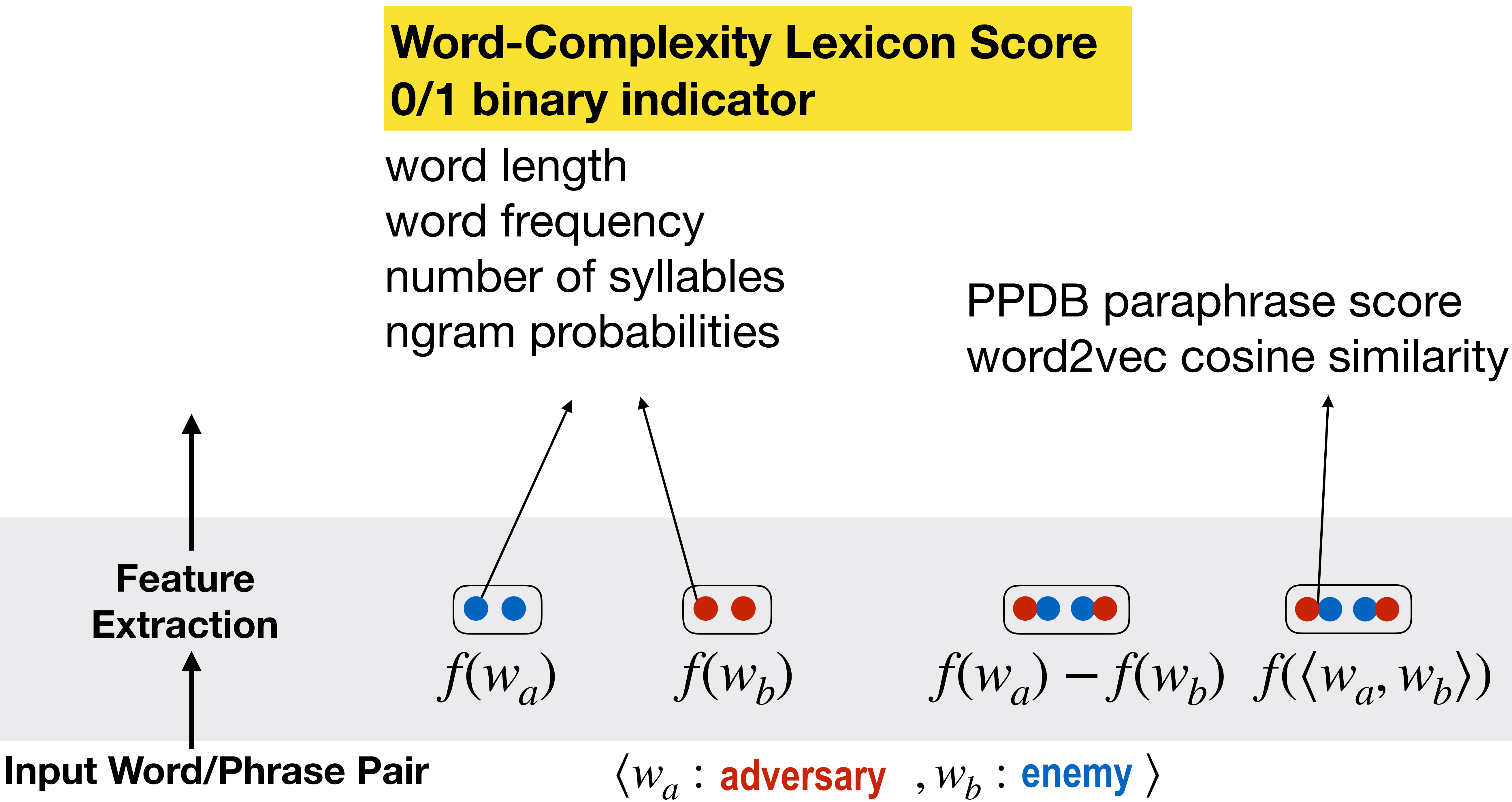
A Pairwise Neural Ranking Model

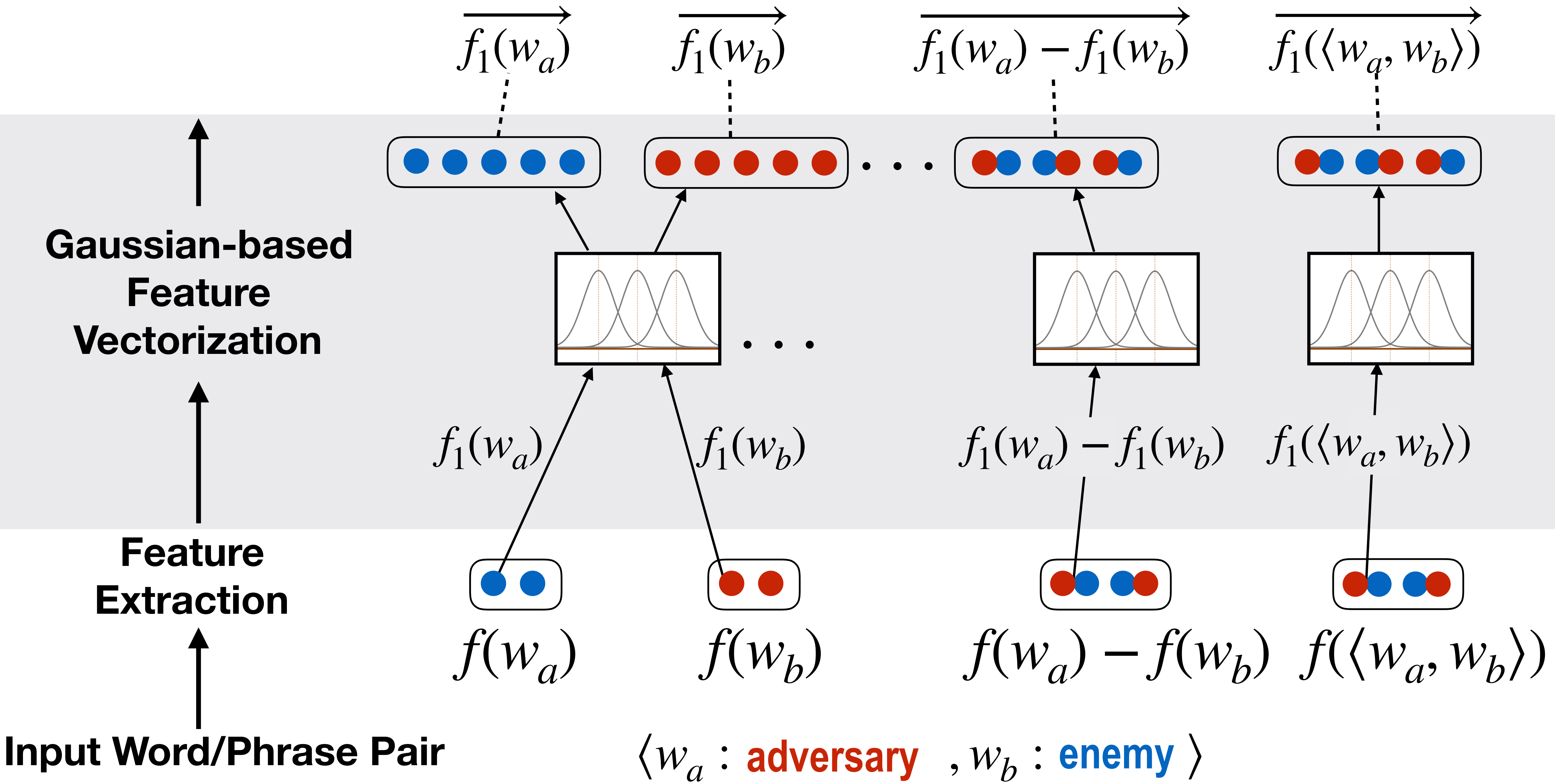

Feature
Extraction
$f(w_a)$
$f(w_b)$
Input Word/Phrase Pair
$\langle w_a$: adversary , w_b : enemy $\rangle$

Word-Complexity Lexicon Score
0/1 binary indicator

word length
word frequency
number of syllables
ngram probabilities




Word-Complexity Lexicon Score
0/1 binary indicator
word length
word frequency
number of syllables
ngram probabilities
PPDB paraphrase score
word2vec cosine similarity
Feature Extraction
$f(w_a)$
$f(w_b)$
$f(w_a) - f(w_b)$
$f(\langle w_a, w_b \rangle)$
Input Word/Phrase Pair
$\langle w_a$: adversary , w_b : enemy $\rangle$



$\overrightarrow{f_1(w_a)}$
$\overrightarrow{f_1(w_b)}$
$\overrightarrow{f_1(w_a) - f_1(w_b)}$
$\overrightarrow{f_1(\langle w_a, w_b \rangle)}$
Gaussian-based Feature Vectorization
$f_1(w_a)$
$f_1(w_b)$
$f_1(w_a) - f_1(w_b)$
$f_1(\langle w_a, w_b \rangle)$
Feature Extraction
$f(w_a)$
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Input Word/Phrase Pair
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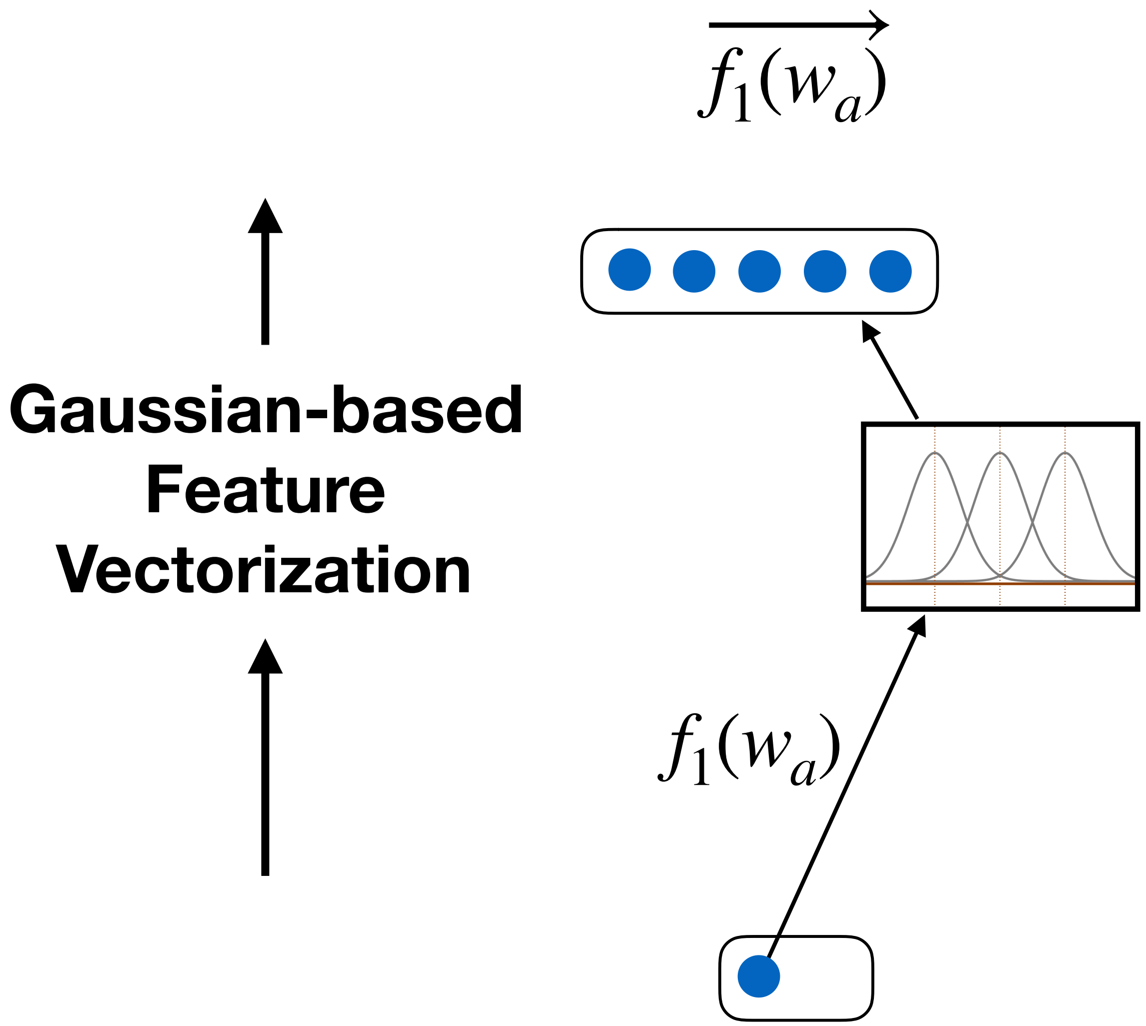
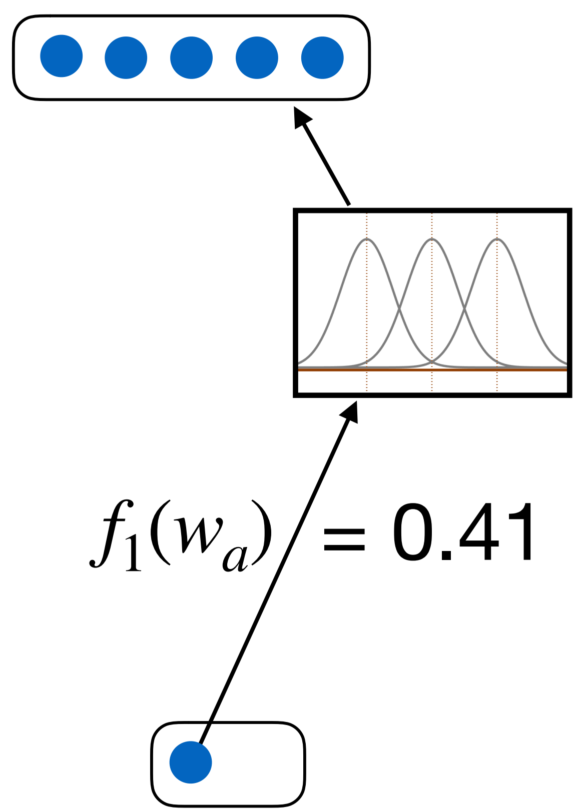
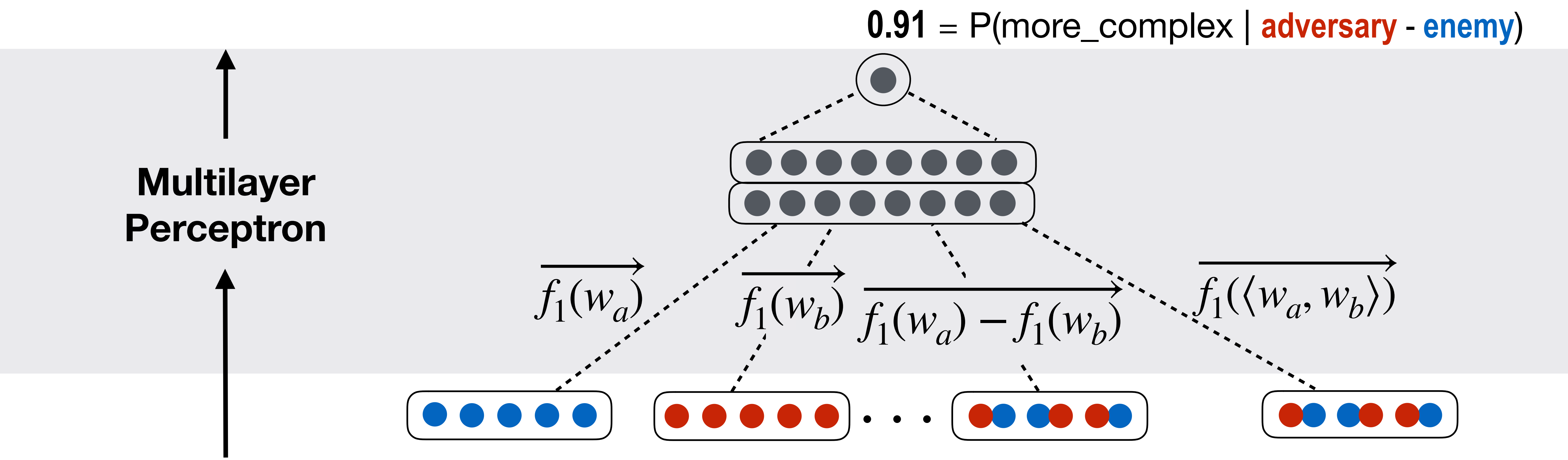

$\overrightarrow{f_1(w_a)}$
Gaussian-based
Feature
Vectorization
$f_1(w_a)$

$$\overrightarrow{f_1(w_a)} = [\ \sim 0.0,\ \mathbf{0.44},\ \mathbf{0.54},\ \sim 0.02,\ \sim 0.0\ ]$$

Gaussian-based Feature Vectorization



$$d_j(f) = e^{-\frac{(f-\mu_j)^2}{2\sigma^2}}$$



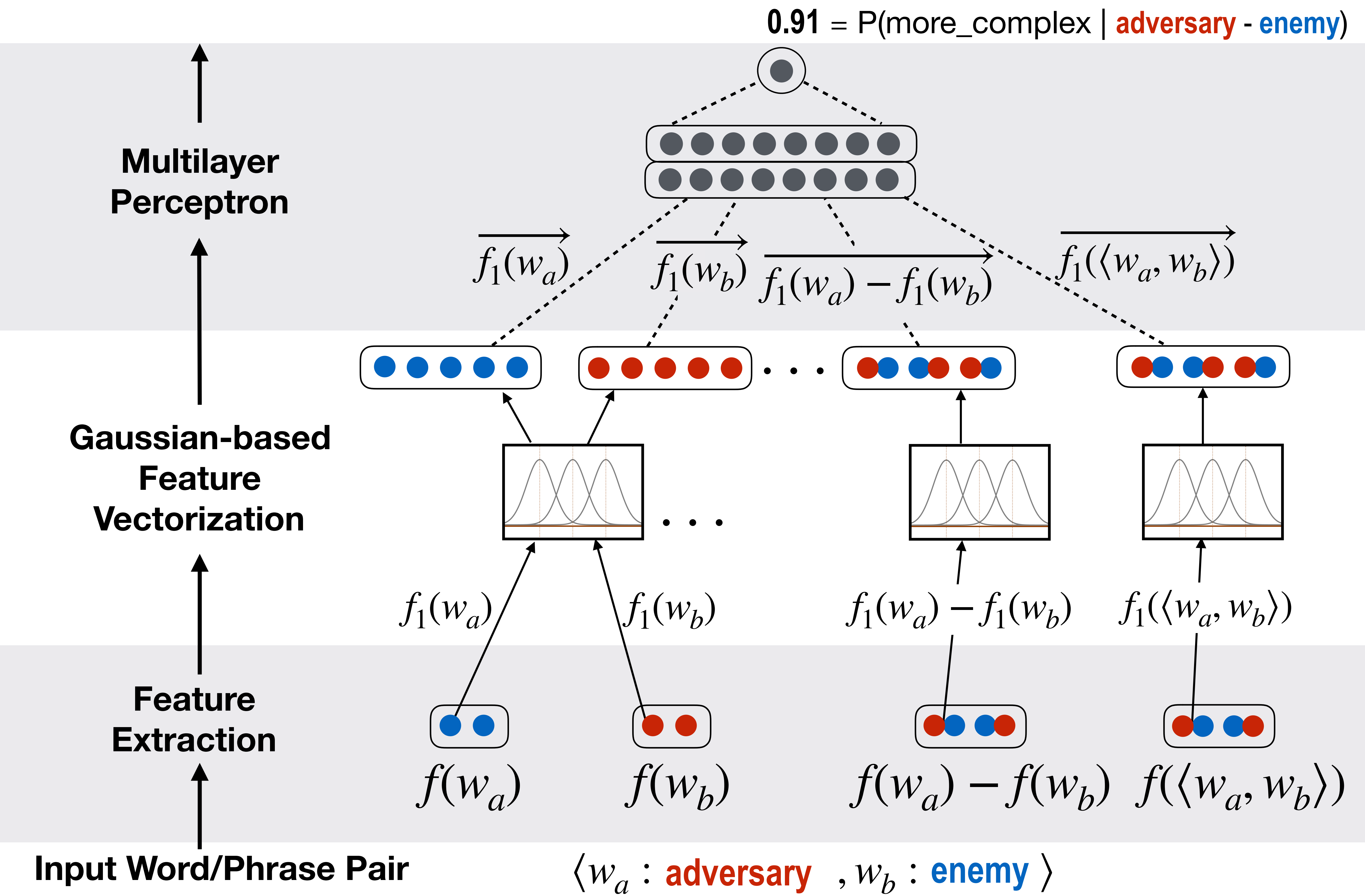
P > 0 $\Rightarrow$ w_a is more complex than w_b

P < 0 $\Rightarrow$ w_a is simpler than w_b

| P | indicates complexity difference

$\langle w_a$: **adversary** , w_b : **enemy** $\rangle$

Neural Readability Ranking Model



Evaluation**

- English Lexical Simplification Shared Task - SemEval 2012
- 300 training sentences, 1710 test sentences

Input	*There were also pieces that would have been **terrible** in any environment.*
(Paetzold & Specia 2017)	**awful, very bad, dreadful**
Our Model + Our Lexicon	**very bad, awful, dreadful**
Gold truth	**very bad, awful, dreadful**

** see paper for full evaluation on 3 lexical simplification tasks and 5 benchmark datasets

Evaluation

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		Precision@1		Pearson	
heuristics	(Biran et al. 2011)	51.3		0.505	
SVM	(Jauhar & Specia 2012)	60.2		0.575	
heuristics	(Kajiwara et al. 2013)	60.4		0.649	
SVM	(Horn et al. 2014)	63.9		0.673	
heuristics	(Glavaš & Štajner 2015)	63.2		0.644	
SVM	(Paetzold & Specia 2015)	65.3	+0.2	0.677	+0.002
neural	(Paetzold & Specia 2017)	65.6		0.679	
			+1.7		+0.035
neural	Our Model + Lexicon + Gaussian	67.3*		0.714*	

* statistically significant ($p < 0.05$) based on the paired bootstrap test

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neural	(Paetzold & Specia 2017)	65.6	0.679
neural	Our Model + Gaussian	66.6	0.702*
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+1.7 +0.035

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Evaluation - Error Analysis

Input	*The colonies of one **strain** appeared smooth.*
(Paetzold & Specia 2017)	***sort, type, breed, variety***
Our Model + Our Lexicon	***type, sort, breed, variety***
Gold truth	***type, sort, variety, breed***

Input	*No damage or **casualties** were reported.*
(Paetzold & Specia 2017)	***injuries, accidents, deaths, fatalities***
Our Model + Our Lexicon	***injuries, deaths, accidents, fatalities***
Gold truth	***deaths, injuries, accidents, fatalities***

SimplePPDB++

- 14.1 million paraphrase rules w/ improved complexity ranking scores

Paraphrase Rule			Score
	→	*self-supporting*	0.93
self-reliant	→	*self-sufficient*	0.48
	→	*self-sustainable* complex	-0.60
	→	*possible*	0.94
viable	→	*realistic*	0.15
	→	*plausible*	-0.91
	→	*in-depth review*	0.89
detailed assessement	→	*careful examination*	0.28
	→	*comprehensive evaluation*	-0.87

Thanks

- **Word-Complexity Lexicon** & **SimplePPDB++** are available!

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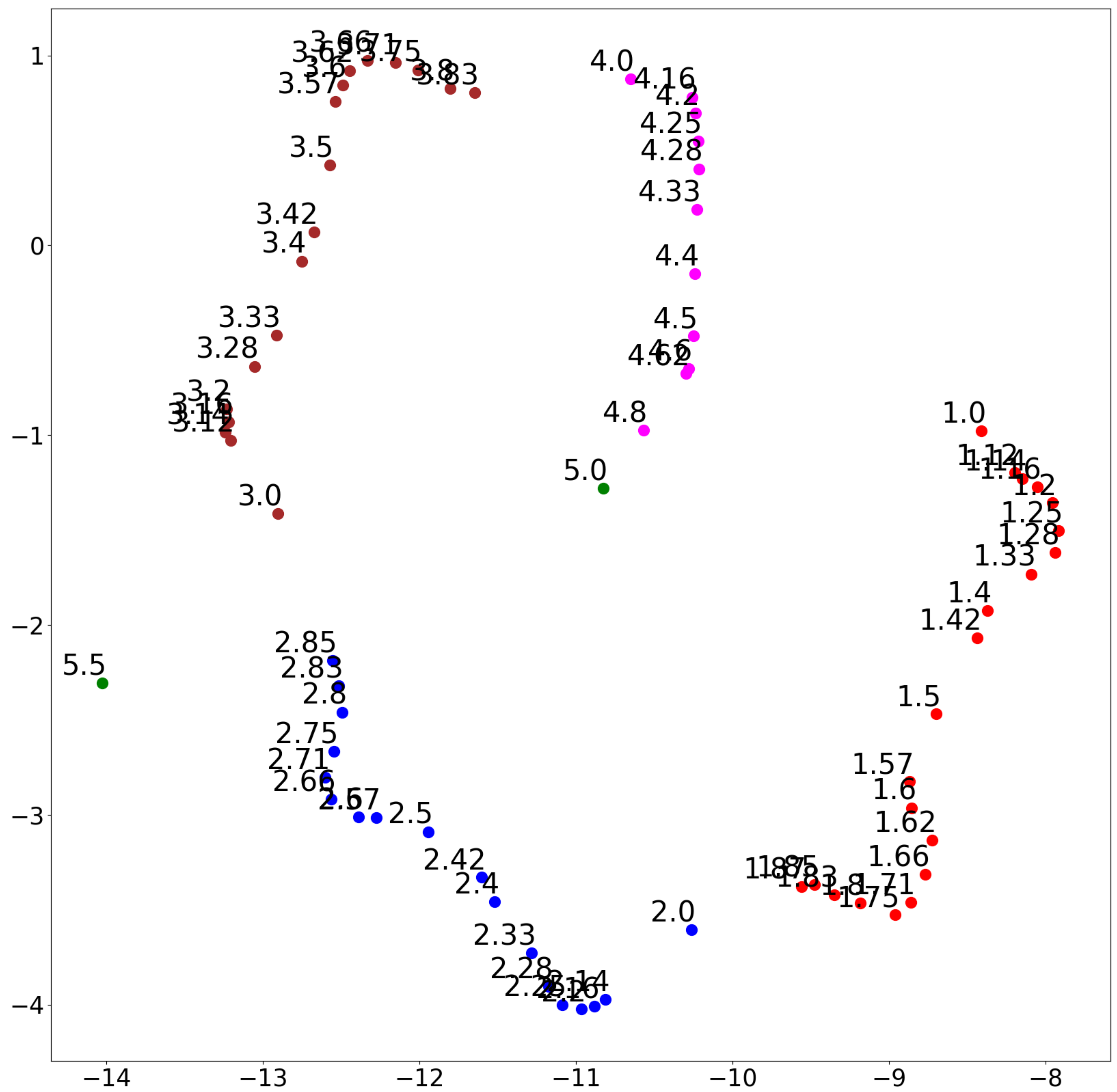
MIN 1 (simple)

MAX 6 (complex)

- PyTorch Code for the **Neural Ranking model** is also available!

  https://github.com/mounicam/lexical_simplification

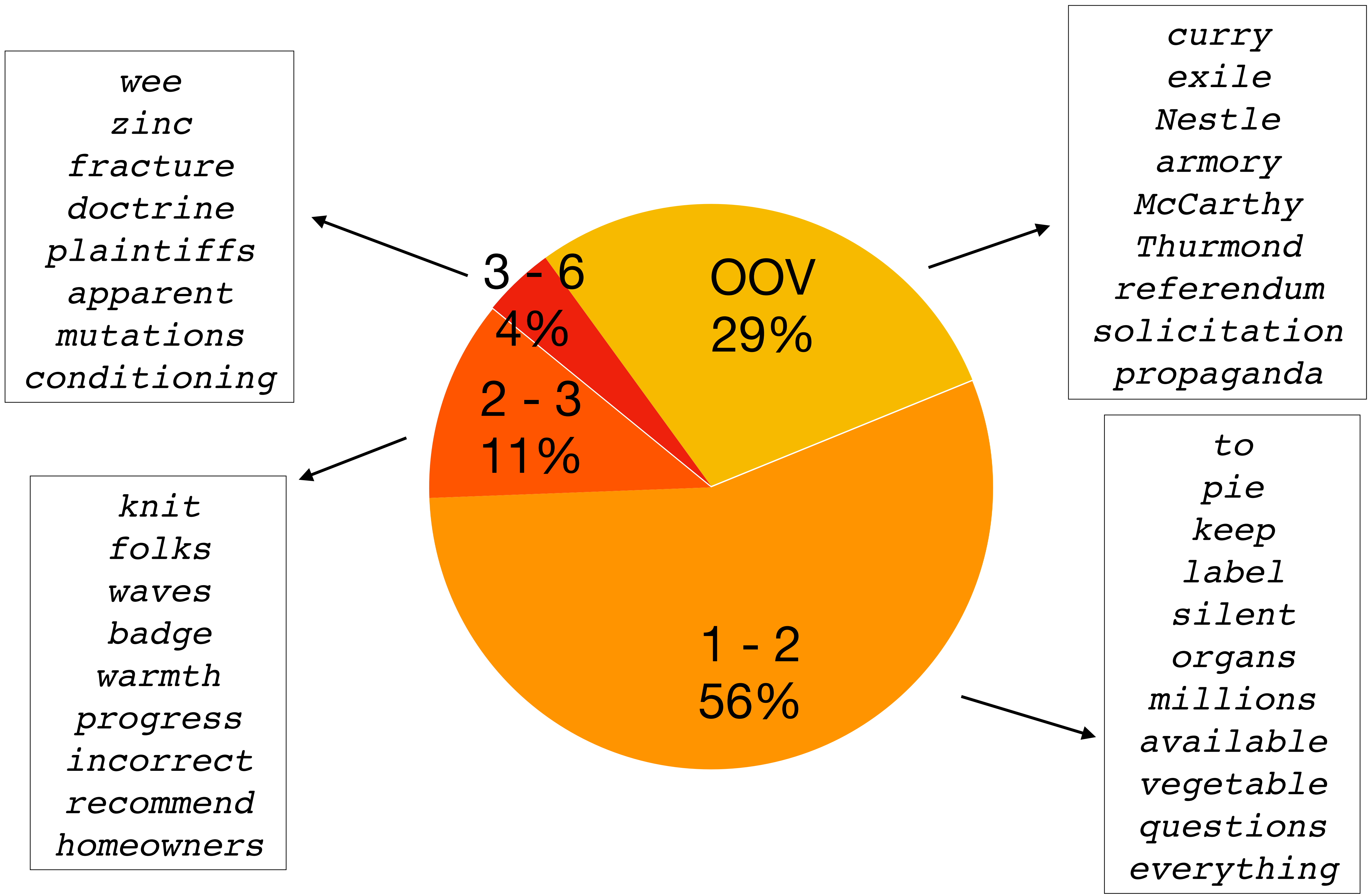
- Contacts: Mounica Maddela & Wei Xu (Ohio State University)



t-SNE visualization of the complexity scores, ranging between 1.0 and 6.0

Word-Complexity Lexicon

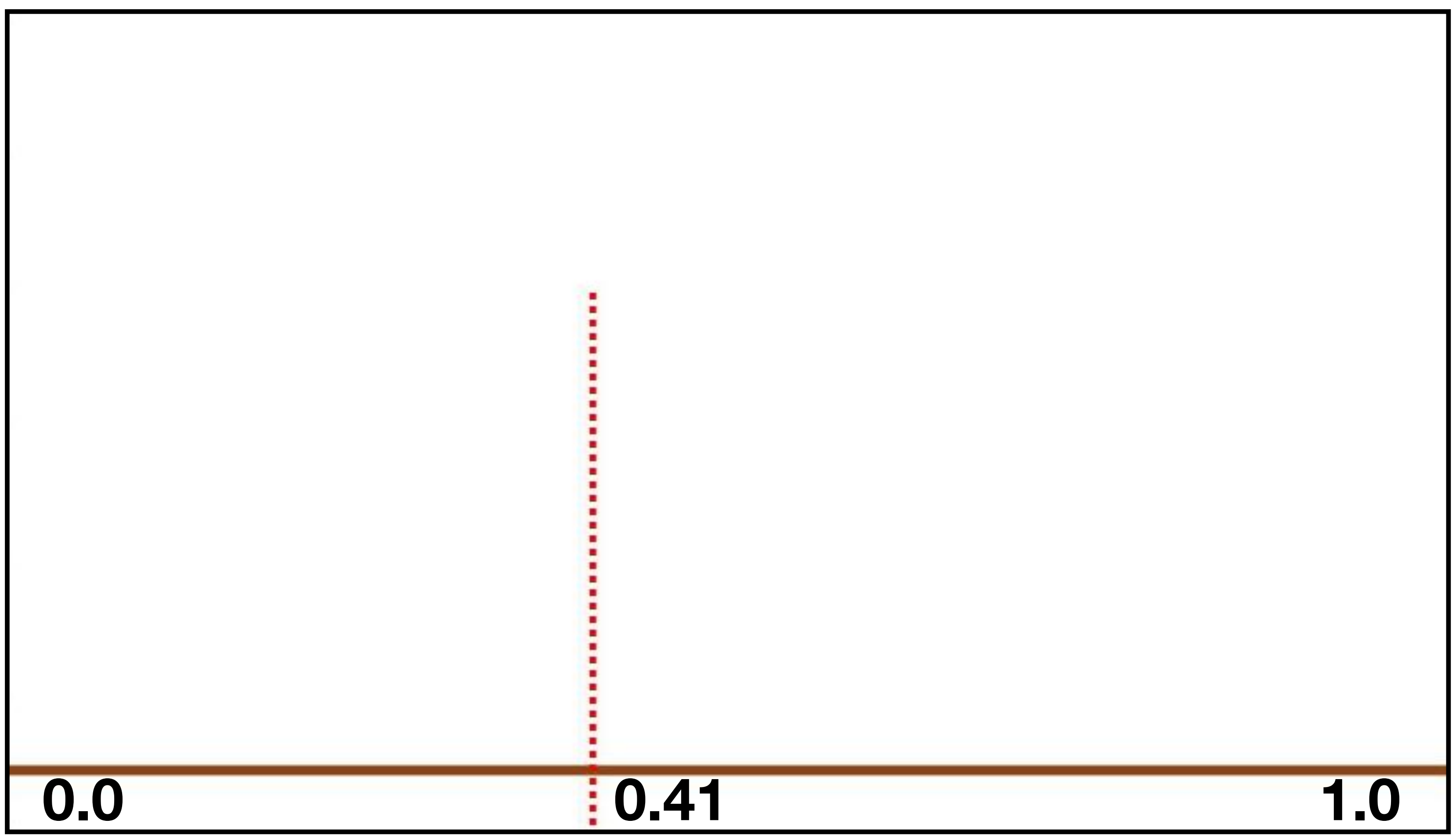
Coverage over Penn Treebank (~1.1 million words)



Gaussian Feature Vectorization

Single feature value : $f(w) = 0.41, \quad f(w) \in [0,1]$

Vectorized feature : $f(w)$ = [~0.0, 0.44, 0.54, ~0.02, ~0.0]



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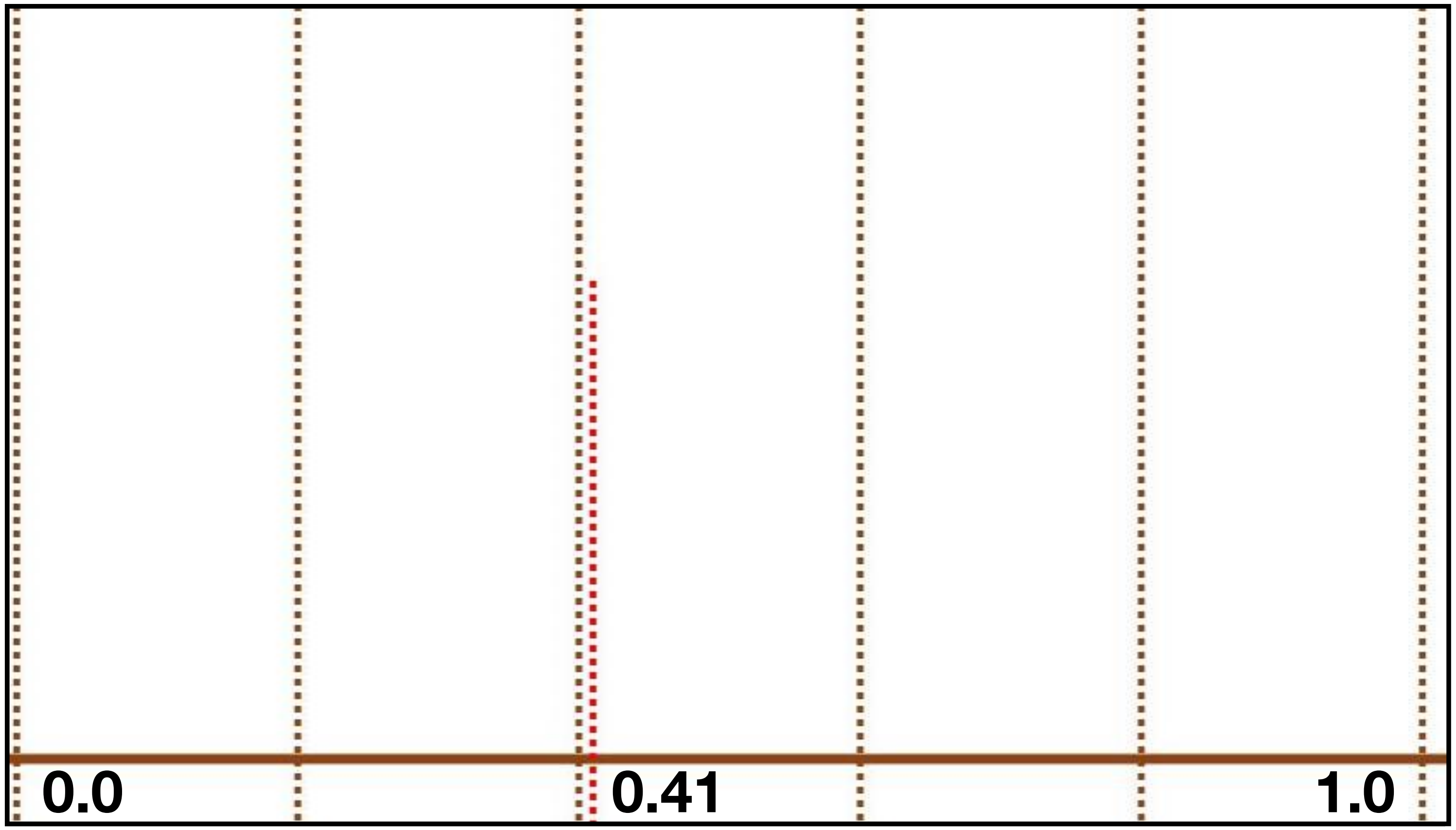

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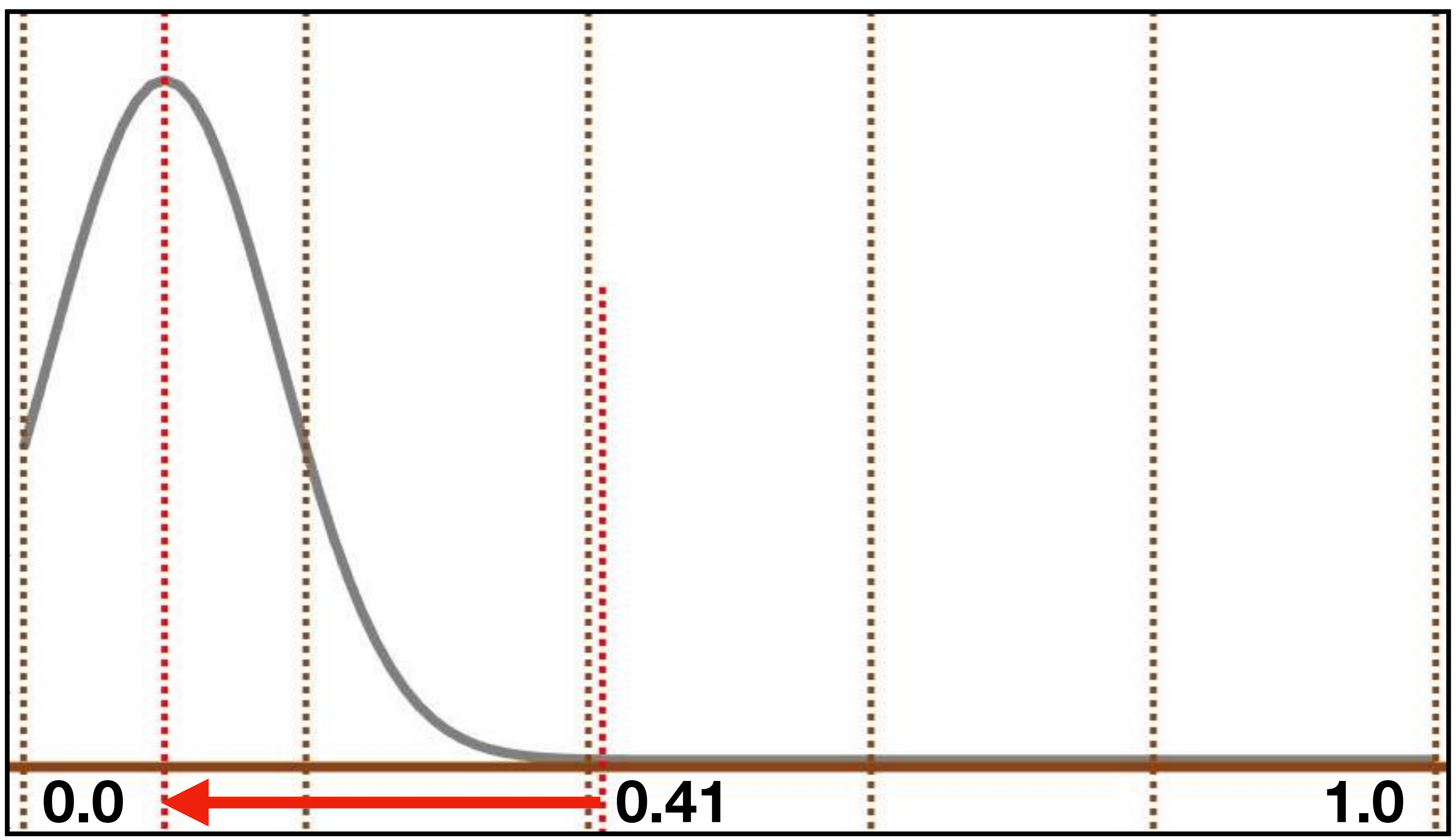

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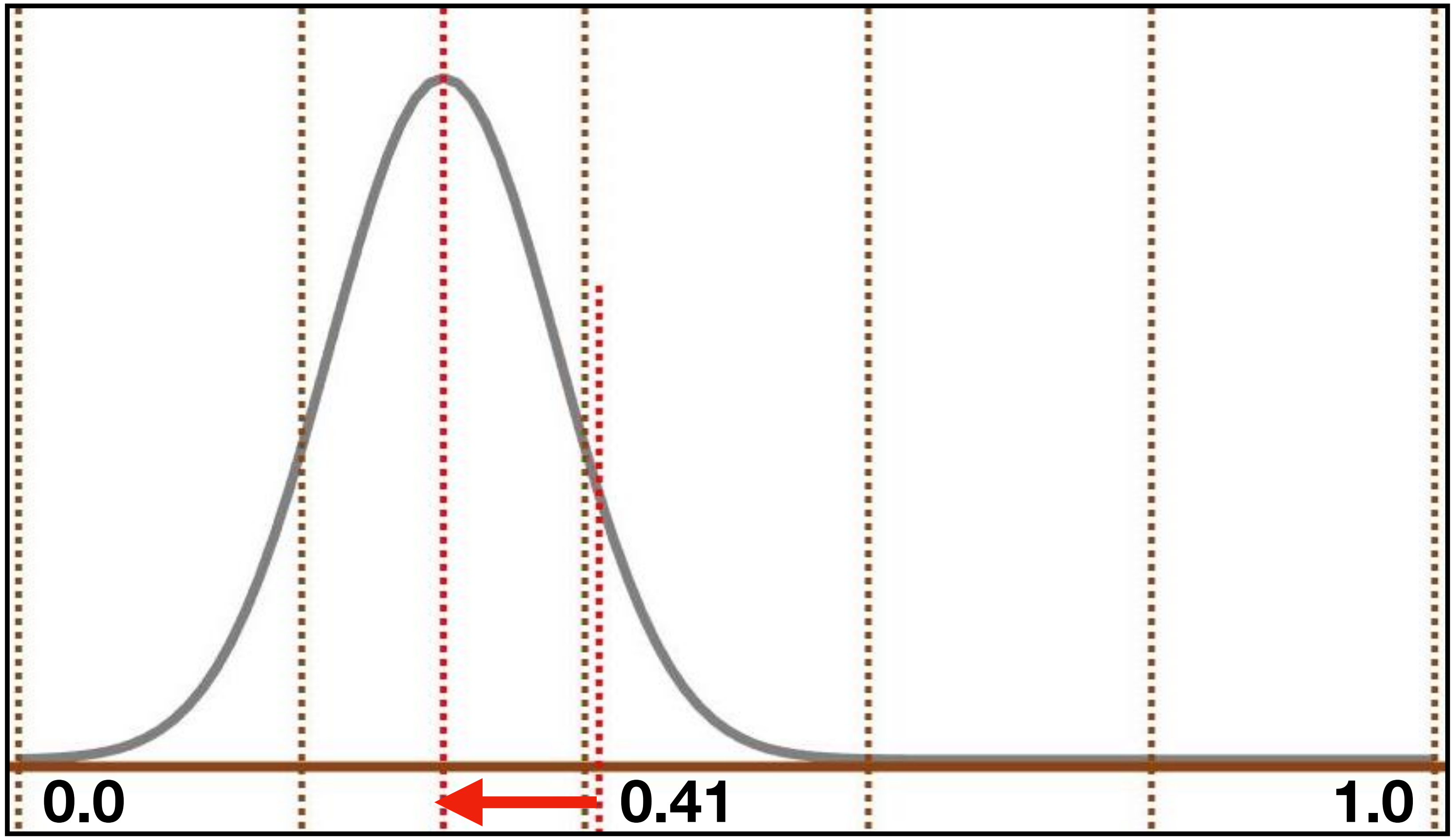

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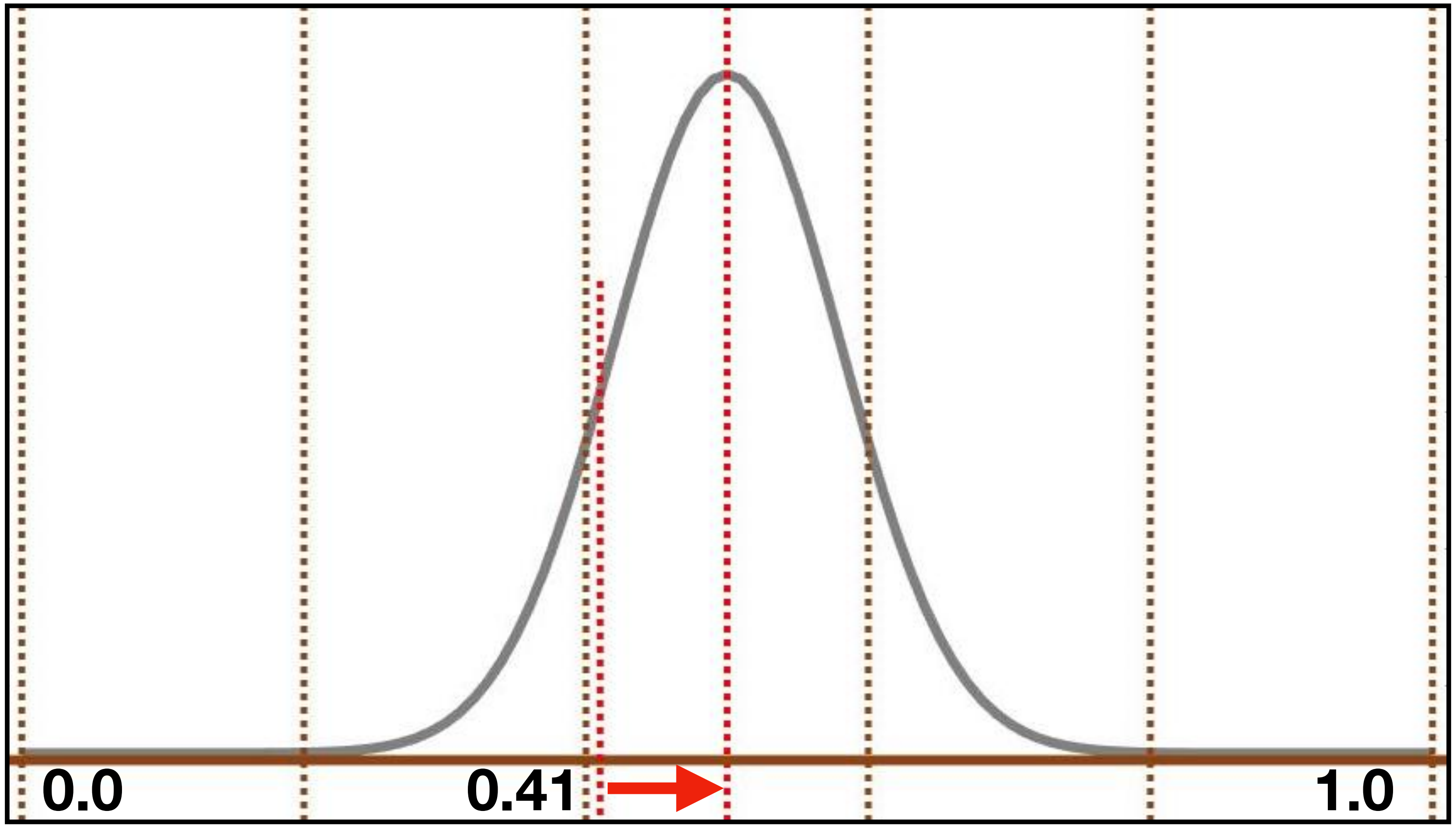

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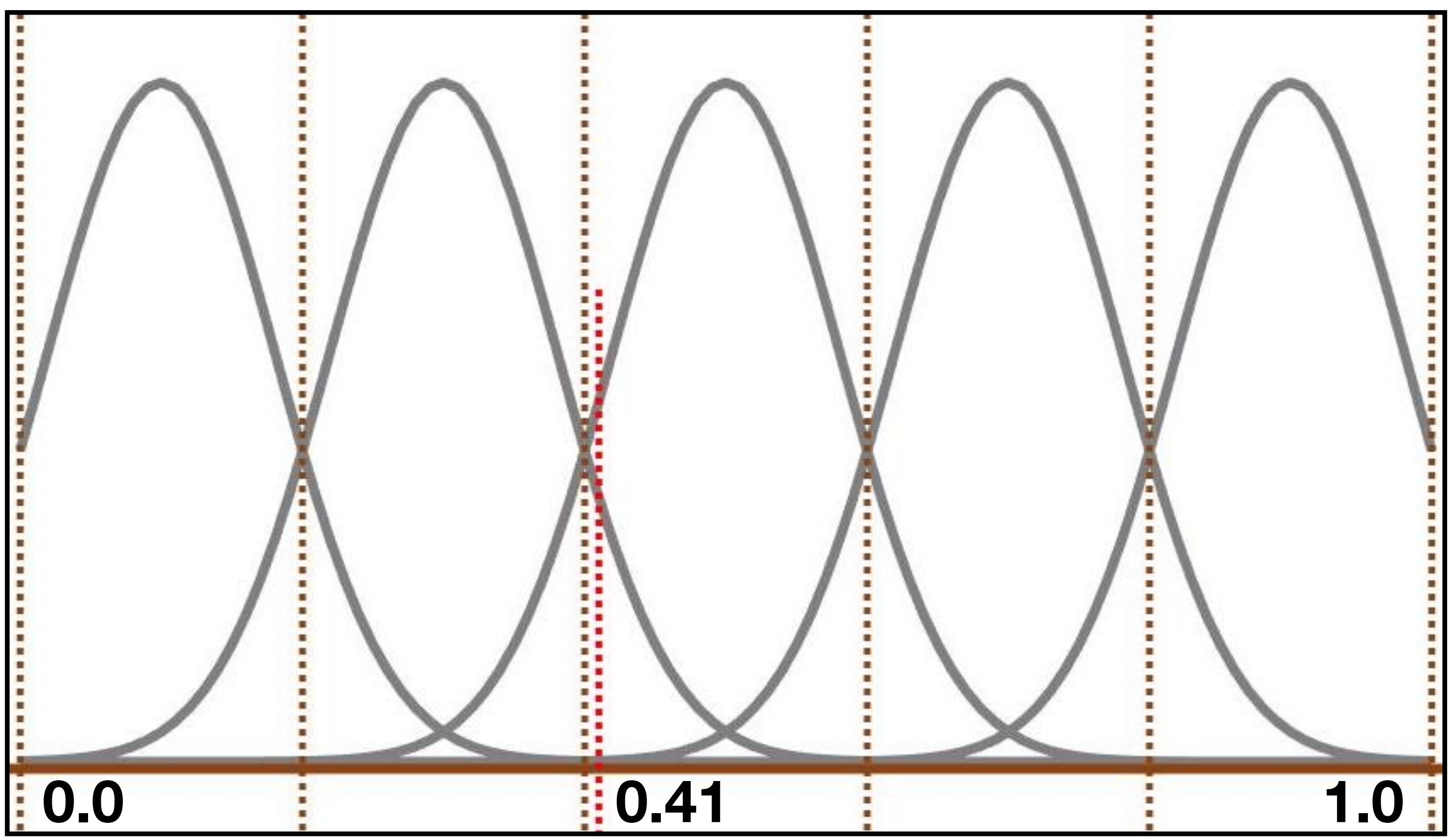

Substitution Ranking - Correct Examples

- Our Model predicts the correct output

Input	*The* ***concept*** *of a "picture element" dates to the earliest days of television.*
(Paetzold & Specia 2017)	***theory, thought, idea***
Our Model + Our Lexicon	***idea, thought, theory***
Gold truth	***idea, thought, theory***

- Our Model handles phrases better than previous SOTA.

Input	*There were also pieces that would have been* ***terrible*** *in any environment.*
(Paetzold & Specia 2017)	***awful, very bad, dreadful***
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Gold truth	***very bad, awful, dreadful***