DSME 6635: Artificial Intelligence for Business Research

Deep-Learning-based NLP: Word2Vec, Evaluations, & Applications

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Agenda

- Word2Vec: Continuous Bag of Words (CBOW), Skip-Gram, GloVe
- Word2Vec Evaluations
- Applications of Word2Vec in Business/Econ Research

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Text as Data

Journal of Economic Literature 2019, 57(3), 535–574
https://doi.org/10.1257/jel.20181020

Text as Data†

Matthew Gentzkow, Bryan Kelly, and Matt Taddy*

An ever-increasing share of human interaction, communication, and culture is recorded as digital text. We provide an introduction to the use of text as an input to economic research. We discuss the features that make text different from other forms of data, offer a practical overview of relevant statistical methods, and survey a variety of applications. (JEL C38, C55, L82, Z13)

0. Pre-processing;

1. Represent raw text $\mathcal{D}$ as a numerical array $\mathbf{C}$;
2. Map $\mathbf{C}$ to predicted values $\hat{\mathbf{V}}$ of unknown outcomes $\mathbf{V}$; and
3. Use $\hat{\mathbf{V}}$ in subsequent descriptive or causal analysis.

3

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NLP Roadmap

Attention is all you need
A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - proceedings.neurips.cc
… the number of **attention** heads and the **attention** key and value dimensions, keeping the amount of computation constant, as described in Section 3.2.2. While single-head **attention** is 0.9 …
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Bert: Pre-training of deep bidirectional transformers for language understanding
J Devlin, MW Chang, K Lee, K Toutanova - arXiv preprint arXiv …, 2018 - arxiv.org
… We introduce **BERT** and its detailed implementation in this … For finetuning, the **BERT** model is first initialized with the pre-trained … , we present **BERT** fine-tuning results on 11 **NLP** tasks. …
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Probability & Vector Representations of NLP → Word2vec & Seq2seq → Transformer-based Models → Large Language Models (LLM)

Before 2010 | 2013-2017 | 2018-2022 | 2023-now

Efficient estimation of word representations in vector space
T Mikolov, K Chen, G Corrado, J Dean - arXiv preprint arXiv:1301.3781, 2013 - arxiv.org
… **vector** X = **vector**("biggest")−**vector**("big") + **vector**("small"). Then, we search in the **vector space** for the **word** … question (we discard the input question **words** during this search). When the …
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[PDF] **Glove: Global vectors** for word representation
J Pennington, R Socher … - Proceedings of the 2014 …, 2014 - aclanthology.org
… We use our insights to construct a new model for word representation which we call **GloVe**, for **Global Vectors**, because the **global** corpus statistics are captured directly by the model. …
☆ Save 99 Cite Cited by 26265 Related articles All 34 versions »

[PDF] Language models are unsupervised multitask learners
A Radford, J Wu, R Child, D Luan, D Amodei … - OpenAI blog, 2019 - persagen.com
Natural language processing tasks, such as question answering, machine translation, reading comprehension, and summarization, are typically approached with supervised learning on taskspecific datasets. We demonstrate that language models begin to learn these tasks without any explicit supervision when trained on a new dataset of millions of webpages called WebText. When conditioned on a document plus questions, the answers generated by the language model reach 55 F1 on the CoQA dataset-matching or exceeding
☆ Save 99 Cite Cited by 2834 Related articles All 16 versions »

Training language models to follow instructions with human feedback
L Ouyang, J Wu, X Jiang, D Almeida… - Advances in …, 2022 - proceedings.neurips.cc
Making language models bigger does not inherently make them better at following a user's intent. For example, large language models can generate outputs that are untruthful, toxic, or simply not helpful to the user. In other words, these models are not aligned with their users. In this paper, we show an avenue for aligning language models with user intent on a wide range of tasks by fine-tuning with human feedback. Starting with a set of labeler-written prompts and prompts submitted through a language model API, we collect a dataset of …
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Word2Vec: Continuous Bag of Words (CBOW)

- References:
  - https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture01-wordvecs1-public.pdf
  - https://web.stanford.edu/class/cs224n/readings/cs224n_winter2023_lecture1_notes_draft.pdf
- So far, our word representations are based on **word-document co-occurrence matrices**.
- Word embedding is a way to obtain word representations via prediction, called **self-supervised learning**.
- Distributional semantics: A word's meaning is provided by the words that **frequently appear close-by**.
- Context of a word w: The set of words that appear **nearby with a fixed window size**.

…government debt problems turning into ***banking*** *crises as happened in 2009…*
…saying that Europe needs unified ***banking*** *regulation to replace the hodgepodge…*
…India has just given its ***banking*** *system a shot in the arm…*

These context words will represent ***banking***

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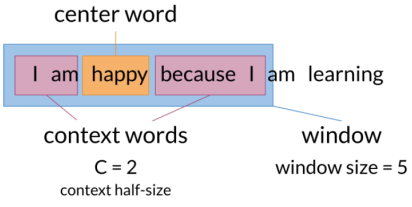
Word2Vec: Continuous Bag of Words (CBOW)

- References:
  - https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture01-wordvecs1-public.pdf
  - https://web.stanford.edu/class/cs224n/readings/cs224n_winter2023_lecture1_notes_draft.pdf
- Continuous Bag of Words (CBOW): Use the outside words (o) to predict the center word (c).
- Skip-gram: Use the **center word (c)** to predict the distribution of **outside words (o)**.

Two embedding matrixes:
context word embedding & center word embedding.



$$\begin{aligned}\text{minimize } J &= -\log P(w_c|w_{c-m},\ldots,w_{c-1},w_{c+1},\ldots,w_{c+m}) \\ &= -\log P(u_c|\hat{v}) \\ &= -\log \frac{\exp(u_c^T\hat{v})}{\sum_{j=1}^{|V|}\exp(u_j^T\hat{v})} \\ &= -u_c^T\hat{v} + \log\sum_{j=1}^{|V|}\exp(u_j^T\hat{v})\end{aligned}$$

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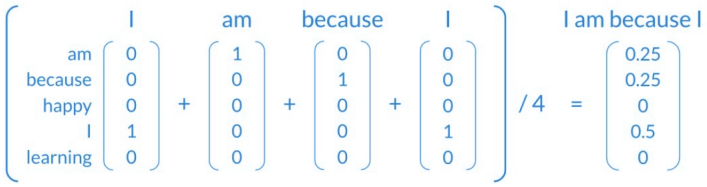
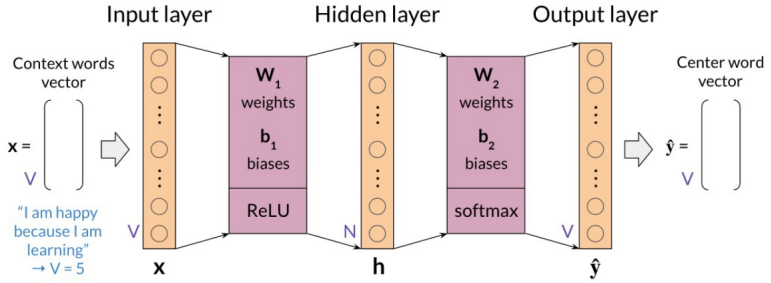
CBOW: Deep Learning Architecture

- References:
  - https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture01-wordvecs1-public.pdf
  - https://web.stanford.edu/class/cs224n/readings/cs224n_winter2023_lecture1_notes_draft.pdf



I am happy because I am learning.

Center Word (c)



Label: Center Word 1-hot.

Loss: Cross entropy.

Use **backpropagation** to estimate the weights and biases.

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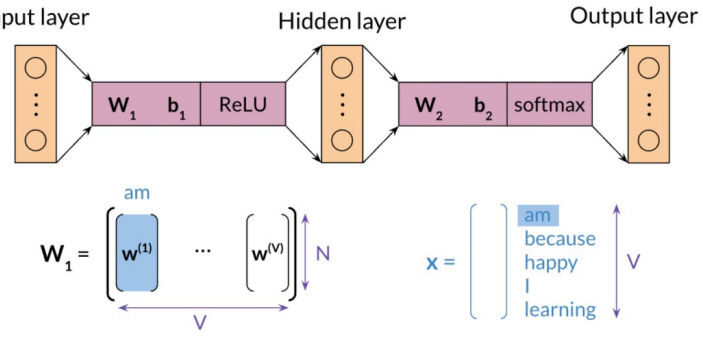
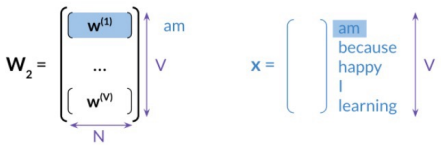
CBOW: Everything Together

1. Convert the text into training data (center word, outside words).
2. Create a 3-layer NN (Dense + ReLU + Softmax)
3. Use back propagation to train the model.
4. Extract the word embeddings with the model.
5. Test the performance of the word embeddings.



If you were to use w_1, each column will correspond to the embeddings of a specific word. You can also use w_2 as follows:



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More on CBOW

- Original code: https://github.com/tmikolov/word2vec
- Trained on Google News Corpus with 6B Tokens (~10Bb)
  - The widely used public data set wikiText 103 has 100M tokens.
  - https://pytorch.org/text/stable/datasets.html#id16
- Trained vectors can be found here:
  - https://github.com/mmihaltz/word2vec-GoogleNews-vectors
- Required computational power:

Efficient estimation of word representations in vector space
T Mikolov, K Chen, G Corrado, J Dean - arXiv preprint arXiv:1301.3781, 2013 - arxiv.org
... vector X = vector("biggest")−vector("big") + vector("small"). Then, we search in the vector space for the word ... question (we discard the input question words during this search). When the ...
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Distributed representations of words and phrases and their compositionality
T Mikolov, I Sutskever, K Chen ... - Advances in neural ..., 2013 - proceedings.neurips.cc
The recently introduced continuous Skip-gram model is an efficient method for learning high-quality distributed vector representations that capture a large number of precise syntactic and semantic word relationships. In this paper we present several improvements that make the Skip-gram model more expressive and enable it to learn higher quality vectors more rapidly. We show that by subsampling frequent words we obtain significant speedup, and also learn higher quality representations as measured by our tasks. We also introduce ...
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NeurIPS 2023 Test-of-Time Award

Table 6: *Comparison of models trained using the DistBelief distributed framework. Note that training of NNLM with 1000-dimensional vectors would take too long to complete.*

Model	Vector Dimensionality	Training words	Accuracy [%]			Training time [days x CPU cores]
			Semantic	Syntactic	Total	
NNLM	100	6B	34.2	64.5	50.8	14 x 180
CBOW	1000	6B	57.3	68.9	63.7	2 x 140
Skip-gram	1000	6B	66.1	65.1	65.6	2.5 x 125

Table 2: *Accuracy on subset of the Semantic-Syntactic Word Relationship test set, using word vectors from the CBOW architecture with limited vocabulary. Only questions containing words from the most frequent 30k words are used.*

Dimensionality / Training words	24M	49M	98M	196M	391M	783M
50	13.4	15.7	18.6	19.1	22.5	23.2
100	19.4	23.1	27.8	28.7	33.4	32.2
300	23.2	29.2	35.3	38.6	43.7	45.9
600	24.0	30.1	36.5	40.8	46.6	50.4

Document → Embedding → Taking Mean → Classification → Sentiment

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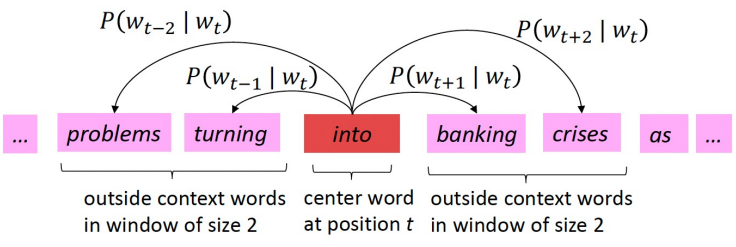
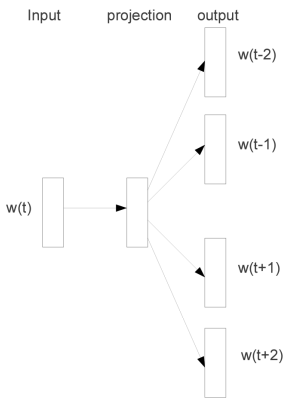
Word2Vec: Skip-Gram

- References:
  - https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture01-wordvecs1-public.pdf
  - https://web.stanford.edu/class/cs224n/readings/cs224n_winter2023_lecture1_notes_draft.pdf
- Skip-gram: Like CBOW but the inverse, using the center word to predict the outside words.

Example windows and process for computing $P(w_{t+j} \mid w_t)$





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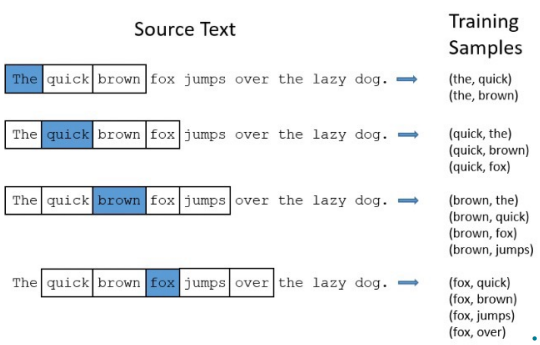
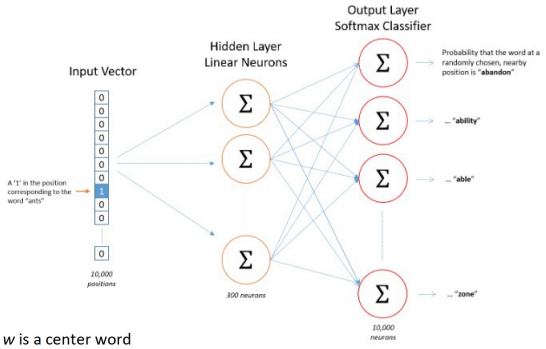
Word2Vec: Skip-Gram

- References:
  - https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture01-wordvecs1-public.pdf
  - https://web.stanford.edu/class/cs224n/readings/cs224n_winter2023_lecture1_notes_draft.pdf





We want to minimize the objective function:

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\le j\le m \\ j\neq 0}} \log P(w_{t+j} \mid w_t;\theta)$$

- v_w when w is a center word
- u_w when w is a context word

Then for a center word c and a context word o:

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w\in V}\exp(u_w^T v_c)}$$

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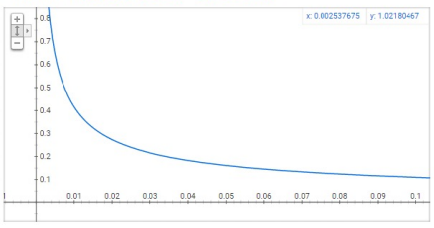
Approximation Training

- References:
  - https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture02-wordvecs2.pdf
  - https://web.stanford.edu/class/cs224n/readings/cs224n_winter2023_lecture1_notes_draft.pdf
- An issue with skip-gram is that computing the probability over **all possible words in the dictionaries** is very **computationally costly** when the dictionary size is large.
- **Subsampling of words**: We do not want to sample the too frequent words (appearing in the neighbor of every word).
  - $P(w_i)$ = the probability word w_i is being kept.
  - $z(w_i)$ = the faction of appearances of word w_i in the corpus.

$$P(w_i) = \left(\sqrt{\frac{z(w_i)}{0.001}} + 1\right)\cdot\frac{0.001}{z(w_i)}$$

Graph for (sqrt(x/0.001)+1)*0.001/x



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Approximation Training

- References:
  - https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture02-wordvecs2.pdf
  - https://web.stanford.edu/class/cs224n/readings/cs224n_winter2023_lecture1_notes_draft.pdf

- **Negative Sampling**: At each observation, we **observe a positive case (numerator)**, and we only use **a small set of negative cases (denominator)** to update the weights, saving a lot of computations.
  - When training the network on the word pair ("fox", "quick"), recall that the "label" or "correct output" of the network is a one-hot vector. That is, for the output neuron corresponding to "quick" to output a 1, and for all the other thousands of output neurons to output a 0.
  - With negative sampling, we are instead going to **randomly select just a small number of "negative" words** (let's say 5) to update the weights for. (In this context, a "negative" word is one for which we want the network to output a 0 for). We will also still update the weights for our "positive" word (which is the word "quick" in our current example).

- **Question**: If your embedding size is 300 and you have 10,000 unique words, when you train on (quick, x), if you don't use negative sampling, how many weights are you updating? If you use 5-word negative sampling, how many weights are you updating?

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Word2Vec: GloVe

[PDF] **Glove**: **Global vectors** for word representation
J Pennington, R Socher... - Proceedings of the 2014 ..., 2014 - aclanthology.org
... We use our insights to construct a new model for word representation which we call **GloVe**, for **Global Vectors**, because the **global** corpus statistics are captured directly by the model. ...
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- References:
  - https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture02-wordvecs2.pdf
  - https://web.stanford.edu/class/cs224n/readings/cs224n-2019-notes02-wordvecs2.pdf

- Global Vectors for Word Representation (GloVe): Word2Vec based on **word co-occurrence matrices**.

- Window-based co-occurrence matrix:

Window length 1 (more common: 5–10)

Symmetric (irrelevant whether left or right context)

Example corpus:

- I like deep learning
- I like NLP
- I enjoy flying

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

Co-occurrence Matrix:

- X: word-word co-occurrence matrix
- X_{ij}: number of times word j occur in the context of word i
- $X_i = \sum_k X_{ik}$: the number of times any word k appears in the context of word i
- $P_{ij} = P(w_j|w_i) = \frac{X_{ij}}{X_i}$: the probability of j appearing in the context of word i

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Word2Vec: GloVe

X_i : number of occurrences of word i in the corpus

- Model: Probability of word j is in word i's context

$$Q_{ij} = \frac{\exp(\vec{u}_j^T \vec{v}_i)}{\sum_{w=1}^{W} \exp(\vec{u}_w^T \vec{v}_i)}$$

- Adjusted Square loss: $\hat{J} = \sum_{i=1}^{W} \sum_{j=1}^{W} X_i (\hat{P}_{ij} - \hat{Q}_{ij})^2$

where $\hat{P}_{ij} = X_{ij}$ and $\hat{Q}_{ij} = \exp(\vec{u}_j^T \vec{v}_i)$

- Some approximations:

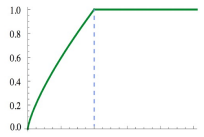
Log transformation is for approximation, simplify the calculation

$$\hat{J} = \sum_{i=1}^{W} \sum_{j=1}^{W} X_i (\log(\hat{P})_{ij} - \log(\hat{Q}_{ij}))^2$$

$$= \sum_{i=1}^{W} \sum_{j=1}^{W} X_i (\vec{u}_j^T \vec{v}_i - \log X_{ij})^2$$

Final Loss Function to Minimize:

Loss: $J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2$

$f \sim$ 

- Fast training
- Scalable to huge corpora

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Agenda

- Word2Vec: Continuous Bag of Words (CBOW), Skip-Gram, GloVe
- Word2Vec Evaluations
- Applications of Word2Vec in Business/Econ Research

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How to Evaluate Language Models?

- Reference: https://web.stanford.edu/class/cs224n/slides/cs224n-2024-lecture02-wordvecs2.pdf
- We know how to evaluate downstream supervised learning tasks with a defined loss function.
- However, what if you are given word vectors or n-gram model, how do you evaluate their performance?
- **Intrinsic Evaluation:**
  - Measure the quality of a model on a **specific/intermediate task independent of any application**.
  - For example, an intrinsic evaluation is analog test. It allows you to capture semantic **analogies** as, "France" is to "Paris" as "Italy" is to <?> and syntactic analogies as "seen" is to "saw" as "been" is to <?>.
  - Fast to compute, helpful to understand the system, but unclear how it correlates with real tasks.
  - Analogies, similarities, etc.
- **Extrinsic Evaluation:**
  - The best way to evaluate the performance of a language model is to embed it in an application and **measure how much the application improves**.
  - **Computationally costly**.
  - Unclear which part of the system (the subsystem or its interactions to other subsystems) should the performance changes be attributed to.
  - **Name Entity Recognition (NER)**, etc.

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Intrinsic Evaluation: Word Analogy

- Word analogy task:

When given a pair of words a and a^* and a third word b, the analogy relationship between a and a^* can be used to find the corresponding word b^* to b. Mathematically, it is expressed as

$$a : a^* :: b : \_\_, \quad (7)$$

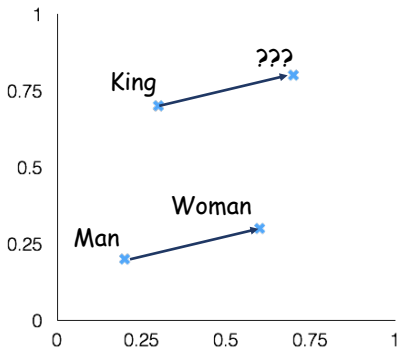
where the blank is b^*. One example could be

$$\text{write} : \text{writing} :: \text{read} : \underline{\text{reading}}. \quad (8)$$

The 3CosAdd method [33] solves for b^* using the following equation:

$$b^* = \underset{b'}{\text{argmax}}(\cos(b', a^* - a + b)), \quad (9)$$

	Word Analogy Datasets							
	Google		Semantic		Syntactic		MSR	
	Add	Mul	Add	Mul	Add	Mul	Add	Mul
SGNS	**71.8**	**73.4**	**77.6**	**78.1**	67.1	**69.5**	**56.7**	**59.7**
CBOW	70.7	70.8	74.4	74.1	**67.6**	68.1	56.2	56.8
GloVe	68.4	68.7	76.1	75.9	61.9	62.7	50.3	51.6
FastText	40.5	45.1	19.1	24.8	58.3	61.9	48.6	52.2
ngram2vec	70.1	71.3	75.7	75.7	65.3	67.6	53.8	56.6
Dict2vec	48.5	50.5	45.1	47.4	51.4	53.1	36.5	38.9



- You should remove the input vectors from the search of b'.
- **Issue**: What if the information is there but nonlinear?
- Datasets: https://aclweb.org/aclwiki/Google_analogy_test_set_(State_of_the_art)

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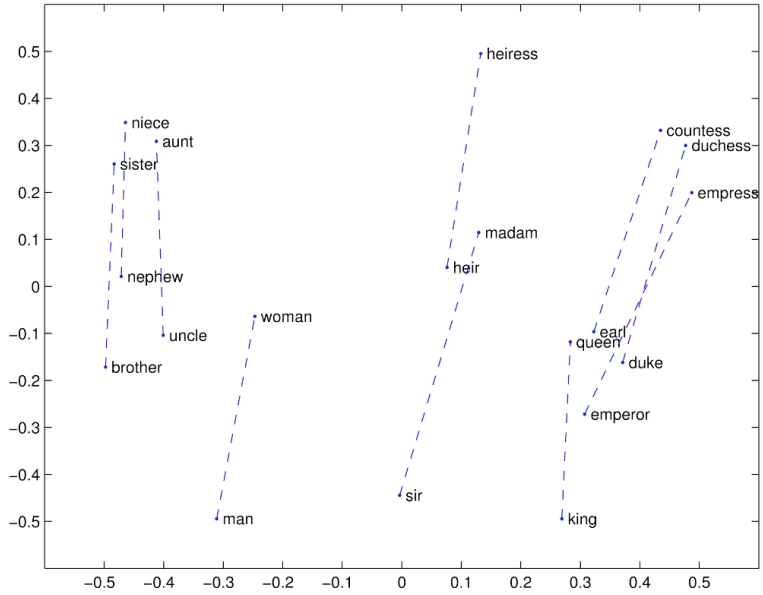
GloVe Analogy Visualization



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Intrinsic Evaluation: Word Similarity

- Given two representations of two words, we can compute their similarities:

$$\cos(w_x, w_y) = \frac{w_x \cdot w_y}{||w_x||\ ||w_y||},$$

- Example dataset: WordSim353: https://www.kaggle.com/datasets/julianschelb/wordsim353-crowd
- The following is a summary of word similarity test datasets:

Word 1	Word 2	Human (mean)
tiger	cat	7.35
tiger	tiger	10
book	paper	7.46
computer	internet	7.58
plane	car	5.77
professor	doctor	6.62
stock	phone	1.62
stock	CD	1.31
stock	jaguar	0.92

TABLE I
WORD SIMILARITY DATASETS USED IN OUR EXPERIMENTS WHERE PAIRS INDICATE THE NUMBER OF WORD PAIRS IN EACH DATASET.

Name	Pairs	Year
WS-353 [40]	353	2002
WS-353-SIM [41]	203	2009
WS-353-REL [41]	252	2009
MC-30 [42]	30	1991
RG-65 [43]	65	1965
Rare-Word (RW) [44]	2034	2013
MEN [45]	3000	2012
MTurk-287 [46]	287	2011
MTurk-771 [47]	771	2012
YP-130 [48]	130	2006
SimLex-999 [49]	999	2014
Verb-143 [50]	143	2014
SimVerb-3500 [51]	3500	2016

Evaluating word embedding models: methods and experimental results
B Wang, A Wang, F Chen, Y Wang… - APSIPA transactions on …, 2019 - cambridge.org
Extensive evaluation on a large number of word embedding models for language processing applications is conducted in this work. First, we introduce popular word embedding models and discuss desired properties of word models and evaluation methods (or evaluators). Then, we categorize evaluators into intrinsic and extrinsic two types. Intrinsic evaluators test the quality of a representation independent of specific natural language processing tasks while extrinsic evaluators use word embeddings as input features to a …
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Intrinsic Evaluation: Correlation

- Word vector distances and correlations with human judgments.

Model	Size	WS353	MC	RG	SCWS	RW
SVD	6B	35.3	35.1	42.5	38.3	25.6
SVD-S	6B	56.5	71.5	71.0	53.6	34.7
SVD-L	6B	65.7	72.7	75.1	56.5	37.0
CBOW†	6B	57.2	65.6	68.2	57.0	32.5
SG†	6B	62.8	65.2	69.7	58.1	37.2
GloVe	6B	65.8	72.7	77.8	53.9	38.1
SVD-L	42B	74.0	76.4	74.1	58.3	39.9
GloVe	42B	**75.9**	**83.6**	**82.9**	**59.6**	**47.8**
CBOW*	100B	68.4	79.6	75.4	59.4	45.5

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Extrinsic Evaluation: Named Entity Recognition

- Named Entity Recognition (NER): Identify the references to a person, location, organization, time, etc. https://en.wikipedia.org/wiki/Named-entity_recognition

Philip lives in Shenzhen and Shanghai in 2024.

Person Location Time

- Use **window classification** with a logistic classifier for NER.
- Classify each human-labeled word using the neighboring words in its context window.

Model	Dev	Test	ACE	MUC7
Discrete	91.0	85.4	77.4	73.4
SVD	90.8	85.7	77.3	73.7
SVD-S	91.0	85.5	77.6	74.3
SVD-L	90.5	84.8	73.6	71.5
HPCA	92.6	**88.7**	81.7	80.7
HSMN	90.5	85.7	78.7	74.7
CW	92.2	87.4	81.7	80.2
CBOW	93.1	88.2	82.2	81.1
GloVe	**93.2**	88.3	**82.9**	**82.2**

Example: Classify "Paris" as +/– location in context of sentence with window length 2:

the museums in Paris are amazing to see .

$X_{window} = [\ x_{museums} \quad x_{in} \quad x_{Paris} \quad x_{are} \quad x_{amazing}\ ]^T$

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Example: GloVe

Analogy

Table 2: Results on the word analogy task, given as percent accuracy. Underlined scores are best within groups of similarly-sized models; bold scores are best overall. HPCA vectors are publicly available[2]; (i)vLBL results are from (Mnih et al., 2013); skip-gram (SG) and CBOW results are from (Mikolov et al., 2013a,b); we trained SG† and CBOW† using the `word2vec` tool[3]. See text for details and a description of the SVD models.

Model	Dim.	Size	Sem.	Syn.	Tot.
ivLBL	100	1.5B	55.9	50.1	53.2
HPCA	100	1.6B	4.2	16.4	10.8
GloVe	100	1.6B	67.5	54.3	60.3
SG	300	1B	61	61	61
CBOW	300	1.6B	16.1	52.6	36.1
vLBL	300	1.5B	54.2	64.8	60.0
ivLBL	300	1.5B	65.2	63.0	64.0
GloVe	300	1.6B	80.8	61.5	70.3
SVD	300	6B	6.3	8.1	7.3
SVD-S	300	6B	36.7	46.6	42.1
SVD-L	300	6B	56.6	63.0	60.1
CBOW†	300	6B	63.6	67.4	65.7
SG†	300	6B	73.0	66.0	69.1
GloVe	300	6B	77.4	67.0	71.7
CBOW	1000	6B	57.3	68.9	63.7
SG	1000	6B	66.1	65.1	65.6
SVD-L	300	42B	38.4	58.2	49.2
GloVe	300	42B	**81.9**	**69.3**	**75.0**

Similarity

Table 3: Spearman rank correlation on word similarity tasks. All vectors are 300-dimensional. The CBOW* vectors are from the `word2vec` website and differ in that they contain phrase vectors.

Model	Size	WS353	MC	RG	SCWS	RW
SVD	6B	35.3	35.1	42.5	38.3	25.6
SVD-S	6B	56.5	71.5	71.0	53.6	34.7
SVD-L	6B	65.7	72.7	75.1	56.5	37.0
CBOW†	6B	57.2	65.6	68.2	57.0	32.5
SG†	6B	62.8	65.2	69.7	58.1	37.2
GloVe	6B	65.8	72.7	77.8	53.9	38.1
SVD-L	42B	74.0	76.4	74.1	58.3	39.9
GloVe	42B	**75.9**	**83.6**	**82.9**	**59.6**	**47.8**
CBOW*	100B	68.4	79.6	75.4	59.4	45.5

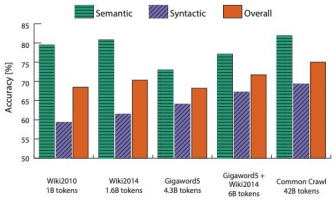

Figure 3: Accuracy on the analogy task for 300-dimensional vectors trained on different corpora.

Analogy

Table 4: F1 score on NER task with 50d vectors. *Discrete* is the baseline without word vectors. We use publicly-available vectors for HPCA, HSMN, and CW. See text for details.

Model	Dev	Test	ACE	MUC7
Discrete	91.0	85.4	77.4	73.4
SVD	90.8	85.7	77.3	73.7
SVD-S	91.0	85.5	77.6	74.3
SVD-L	90.5	84.8	73.6	71.5
HPCA	92.6	**88.7**	81.7	80.7
HSMN	90.5	85.7	78.7	74.7
CW	92.2	87.4	81.7	80.2
CBOW	93.1	88.2	82.2	81.1
GloVe	**93.2**	88.3	**82.9**	**82.2**

NER

[PDF] **Glove**: Global vectors for word representation
J Pennington, R Socher… - Proceedings of the 2014 …, 2014 - aclanthology.org
… **GloVe**, … **GloVe** model outperforms all other methods on all evaluation metrics, except for the CoNLL test set, on which the HPCA method does slightly better. We conclude that the **GloVe** …
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Agenda

- Word2Vec: Continuous Bag of Words (CBOW), Skip-Gram, GloVe
- Word2Vec Evaluations
- Applications of Word2Vec in Business/Econ Research

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Application: Text Algorithms in Economics

Annual Review of Economics

Text Algorithms in Economics

Elliott Ash[1] and Stephen Hansen[2,3]

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Keywords

text as data, topic models, word embeddings, large language models, transformer models

Abstract

This article provides an overview of the methods used for algorithmic text analysis in economics, with a focus on three key contributions. First, we introduce methods for representing documents as high-dimensional count vectors over vocabulary terms, for representing words as vectors, and for representing word sequences as embedding vectors. Second, we define four core empirical tasks that encompass most text-as-data research in economics and enumerate the various approaches that have been taken so far to accomplish these tasks. Finally, we flag limitations in the current literature, with a focus on the challenge of validating algorithmic output.

Text algorithms in economics
E Ash, S Hansen - Annual Review of Economics, 2023 - annualreviews.org
... methods used for algorithmic text analysis in economics, with ... encompass most text-as-data research in economics and ... with a focus on the challenge of validating algorithmic output. ...
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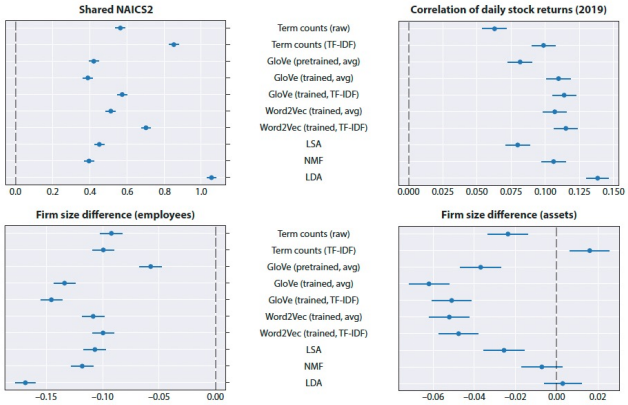
- **Four problems**: (I) Measuring document similarity; (II) Concept detection; (III) How concepts are related; (IV) Associating text with metadata.
- **Two challenges**: (I) Validation; (II) Interpretability.
- **One future**: Large Language Models.



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Validation problem: Which result should we believe when the coefficients using diff embeddings are inconsistent?

Application: Corporate Culture Measurement

The Review of Financial Studies

Measuring Corporate Culture Using Machine Learning

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We create a culture dictionary using one of the latest machine learning techniques—the word embedding model—and 209,480 earnings call transcripts. We score the five corporate cultural values of *innovation, integrity, quality, respect*, and *teamwork* for 62,664 firm-year observations over the period 2001–2018. We show that an innovative culture is broader than the usual measures of corporate innovation – R&D expenses and the number of patents. Moreover, we show that corporate culture correlates with business outcomes, including operational efficiency, risk-taking, earnings management, executive compensation design, firm value, and deal making, and that the culture-performance link is more pronounced in bad times. Finally, we present suggestive evidence that corporate culture is shaped by major corporate events, such as mergers and acquisitions. (*JEL* C45, G34, M14)

Received February 15, 2019; editorial decision May 26, 2020 by Editor Itay Goldstein. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

- Train word embeddings using word2vec on earnings call transcripts.
- Create a culture dictionary based on the associations of different words/phrases and the "value words" (*innovation, integrity, quality, respect, and teamwork*) under the trained word embeddings.
- **Business implications**: A strong corporate culture correlates with greater operational efficiency, more risk-taking, less earnings management, and higher firm value.

Measuring corporate culture using machine learning
K Li, F Mai, R Shen, X Yan
The Review of Financial Studies, 2021 · academic.oup.com

Abstract
We create a culture dictionary using one of the latest machine learning techniques—the word embedding model—and 209,480 earnings call transcripts. We score the five corporate cultural values of *innovation, integrity, quality, respect*, and *teamwork* for 62,664 firm-year observations over the period 2001–2018. We show that an innovative culture is broader than the usual measures of corporate innovation – R&D expenses and the number of patents. Moreover, we show that corporate culture correlates with business

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Application: Product2Vec

Product2Vec: Leveraging representation learning to model consumer product choice in large assortments

NYU Stern School of Business

83 Pages • Posted: 7 Feb 2020 • Last revised: 3 Jul 2022

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Date Written: July 1, 2022

Abstract

We propose a method, Product2Vec, based on representation learning, that can automatically learn latent product attributes that drive consumer choices, to study product-level competition when the number of products is large. We demonstrate Product2Vec's interpretability and capability for scalable causal inference. For interpretability, first, we theoretically demonstrate that there exists a direct link between product vectors and product attributes by deriving a formal proof. Second, we use product embedding to create two metrics, complementarity and exchangeability, that allow us to distinguish between products that are complements and substitutes, respectively. For causal inference, we combine product vectors with choice models and show that we can achieve better accuracy—both in terms of model fit and unbiased price coefficients—when compared to a model based solely on observable attributes, and obtain results similar to those obtained with a more complex model that includes a fixed effect for every product.

Keywords: machine learning, product competition, representation learning, choice models

- Leverage the idea of skip-gram to learn the latent product embeddings based on other products in the choice set.
- **Interpretability**: A theoretical proof on the link between product embeddings, product attributes, and product clusters; metrics of complementarity and exchangeability.
- **Causal inference**: Combining product embeddings and choice models achieves better accuracy in model fit and unbiased price coefficients estimation.

Product2Vec: Leveraging representation learning to model consumer product choice in large assortments

F Chen, X Liu, D Proserpio… - NYU Stern School of …, 2022 - papers.ssrn.com

We propose a method, **Product2Vec**, based on representation learning, that can automatically learn latent product attributes that drive consumer choices, to study product-level …

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Application: Product2Vec-Email

RESEARCH-ARTICLE

E-commerce in Your Inbox: Product Recommendations at Scale

Authors: Mihajlo Grbovic, Vladan Radosavljevic, Nemanja Djuric, Narayan Bhamidipati, Jaikit Savla, Varun Bhagwan, Doug Sharp Authors Info & Claims

KDD '15: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining • August 2015 • Pages 1809–1818 • https://doi.org/10.1145/2783258.2788627

Published: 10 August 2015 Publication History Check for updates

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ABSTRACT

In recent years online advertising has become increasingly ubiquitous and effective. Advertisements shown to visitors fund sites and apps that publish digital content, manage social networks, and operate e-mail services. Given such large variety of internet resources, determining an appropriate type of advertising for a given platform has become critical to financial success. Native advertisements, namely ads that are similar in look and feel to content, have had great success in news and social feeds. However, to date there has not been a winning formula for ads in e-mail clients. In this paper we describe a system that leverages user purchase history determined from e-mail receipts to deliver highly personalized product ads to Yahoo Mail users. We propose to use a novel neural language-based algorithm specifically tailored for delivering effective product recommendations, which was evaluated against baselines that included showing popular products and products predicted based on co-occurrence. We conducted rigorous offline testing using a large-scale product purchase data set, covering purchases of more than 29 million users from 172 e-commerce websites. Ads in the form of product recommendations were successfully tested on online traffic, where we observed a steady 9% lift in click-through rates over other ad formats in mail, as well as comparable lift in conversion rates. Following successful tests, the system was launched into production during the holiday season of 2014.

- Leverage the idea of skip-gram to learn the latent product embeddings based on purchases from email promotions.
- Train both product2vec and user2vec.
- **Impact**: 9%+ lift in CTR; launched into production.

click through rate increase normally less than 1%

E-commerce in your inbox: Product recommendations at scale

M Grbovic, V Radosavljevic, N Djuric, N Bhamidipati, J Savla, V Bhagwan, D Sharp

Proceedings of the 21th ACM SIGKDD international conference on knowledge …, 2015 dl.acm.org

In recent years online advertising has become increasingly ubiquitous and effective. Advertisements shown to visitors fund sites and apps that publish digital content, manage social networks, and operate e-mail services. Given such large variety of internet resources, determining an appropriate type of advertising for a given platform has become critical to financial success. Native advertisements, namely ads that are similar in look and feel to content, have had great success in news and social feeds. However, to date there

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Other Applications of Product2Vec

P2V-MAP: Mapping market structures for large retail assortments
S Gabel, D Guhl, D Klapper
Journal of Marketing Research, 2019 · journals.sagepub.com

The authors propose a new, exploratory approach for analyzing market structures that leverages two recent methodological advances in natural language processing and machine learning. They customize a neural network language model to derive latent product attributes by analyzing the co-occurrences of products in shopping baskets. Applying dimensionality reduction to the latent attributes yields a two-dimensional product map. This method is well-suited to retailers because it relies on data that are readily

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Scalable bundling via dense product embeddings
M Kumar, D Eckles, S Aral
arXiv preprint arXiv:2002.00100, 2020 · arxiv.org

Bundling, the practice of jointly selling two or more products at a discount, is a widely used strategy in industry and a well examined concept in academia. Historically, the focus has been on theoretical studies in the context of monopolistic firms and assumed product relationships, e.g., complementarity in usage. We develop a new machine-learning-driven methodology for designing bundles in a large-scale, cross-category retail setting. We leverage historical purchases and consideration sets created from clickstream data to

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Item2vec: neural item embedding for collaborative filtering
O Barkan, N Koenigstein
2016 IEEE 26th International Workshop on Machine Learning for …, 2016 · ieeexplore.ieee.org

Many Collaborative Filtering (CF) algorithms are item-based in the sense that they analyze item-item relations in order to produce item similarities. Recently, several works in the field of Natural Language Processing (NLP) suggested to learn a latent representation of words using neural embedding algorithms. Among them, the Skip-gram with Negative Sampling (SGNS), also known as word2vec, was shown to provide state-of-the-art results on various linguistics tasks. In this paper, we show that item-based CF can be cast in the

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