

# INTELIGENȚĂ , ARTIFICIALĂ



**Sisteme inteligente**

Sisteme care învață singure

– generative AI–

**Laura Dioșan**

# Sumar

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## A. Scurtă introducere în Inteligența Artificială (IA)

## C. Sisteme inteligente

### ■ Sisteme care învață singure

- Arbori de decizie
- **Rețele neuronale artificiale**
- kNN
- Algoritmi evolutivi
- Mașini cu suport vectorial

### ■ Sisteme bazate pe reguli

### ■ Sisteme hibride

## B. Rezolvarea problemelor prin căutare

### ■ Definirea problemelor de căutare

### ■ Strategii de căutare

- Strategii de căutare neinformate
- Strategii de căutare informate
- Strategii de căutare locale (Hill Climbing, Simulated Annealing, Tabu Search, Algoritmi evolutivi, PSO, ACO)
- Strategii de căutare adversială

# Materiale de citit și legături utile

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- ❑ <https://www.tensorflow.org/text/tutorials/word2vec>
- ❑ <https://radimrehurek.com/gensim/models/word2vec.html>
- ❑ <https://www.ruder.io/word-embeddings-1/>
- ❑ <https://aylien.com/blog/a-review-of-the-recent-history-of-natural-language-processing?ref=ruder.io>
- ❑ <https://nlp.stanford.edu/~manning/> - *a lot of lectures about NLP*

# De ce reprezentari vectoriale ale intelesului unui cuvant/text?

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- Permit determinarea similaritatii intre cuvinte/texte
  - **fast** is similar to **rapid**
  - **tall** is similar to **height**

Question answering:

➤Q: "How **tall** is Mt. Everest?"

Candidate A: "The official **height** of Mount Everest is 29029 feet"

# Intuitia din spatele similaritatii

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## □ Exemplu: Ce este o Sirrus X 3.0?

*The **Sirrus X 3.0** invites you to explore beyond boundaries. With confidence-inspiring tires, an upright riding position, and intuitive components, **Sirrus X 3.0** is your ticket to adventure.*

## □ Din context, o persoana poate ghici ca Sirrus X 3.0 este un model de bicicleta

## □ Pentru un algoritm, intuitia e ca **doua cuvinte sunt similar daca ele sunt folosite in context similar**

# Diferite reprezentari vectoriale pentru text

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## □ Reprezentari rare (*sparse*):

1. Mutual-information weighted word co-occurrence matrices

## □ Reprezentari dense (compacte) :

2. Singular Value Decomposition (si Latent Semantic Analysis)
3. Neural-network-inspired models (skip-grams, CBOW)
4. Altele (e.g. brown clusters)

# Vectori rari vs. densi

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- ❑ Vectorii → matricea de co-ocurență a termenilor
  - **lungi** (length  $|V| = 20,000 \rightarrow 50,000$ )
  - **rari** (f multe elemente sunt 0)
- ❑ Alternativa: vectori învățați (prin AI/ML)
  - scurți (length 200-1000)
  - **densi** (multe elemente nu sunt 0)
- ❑ De ce vectori densi?
  - Vectorii scurți → folosiți mai ușor ca și *features* în algoritmi de învățare (mai puțini coeficienți de învățat)
  - Vectorii densi pot generaliza mai bine, captând sinonimia termenilor
    - Bike – scooter
    - Car – automobile
    - House – apartment

# Modele de predicție (învățare) a reprezentărilor

## □ Evoluție

### ■ Word-level

- 2003 - N-gram Neural language model (Montreal - Bengio)
  - <https://www.jmlr.org/papers/volume3/bengio03a/bengio03a.pdf>
  - Probability of the target word based on previous k words
  - Estimation of the probability by an ANN -> prediction of the next word in a sequence
- 2008 - multi-task model (Princeton - Collobert)
  - [https://ronan.collobert.com/pub/matos/2008\\_nlp\\_icml.pdf](https://ronan.collobert.com/pub/matos/2008_nlp_icml.pdf)
  - Probability of MORE target words (a sequence of words)
  - Estimation of the probability by an ANN -similar to Bengio's model,
- 2013 - word2vec (Google - Mikolov)
  - <https://papers.nips.cc/paper/2013/file/9aa42b31882ec039965f3c4923ce901b-Paper.pdf>
  - Continuous BOW model -> try to predict a word based on its context (neighbours); input = neighbour words, output = target word
  - Skip-gram model -> try to predict context (neighbours) of a word; input = target word; output = neighbour words;
  - Visualisation of embeddings <https://ronxin.github.io/wevi/>
  - Trained vectors <https://radimrehurek.com/gensim/models/word2vec.html> or <https://github.com/3Top/word2vec-api#where-to-get-a-pretrained-models>

### ■ Sentence (document) level (2014 - ... )

- 2014 - Paragraph embedding <https://arxiv.org/abs/1405.4053>

### ■ Contextual word-vectors (Word vectors compress all contexts into a *single* vector) (2016 - ...)

- 2016 context2vec <https://www.aclweb.org/anthology/K16-1006.pdf>
- 2017 tagLM <https://arxiv.org/abs/1705.00108>
- 2017 CoVe <https://papers.nips.cc/paper/2017/hash/20c86a628232a67e7bd46f76fba7ce12-Abstract.html>
- 2018 ELMo <https://www.aclweb.org/anthology/N18-1202/>
- 2018 ULMFiT <https://arxiv.org/abs/1801.06146>
- 2019 BERT <https://arxiv.org/abs/1810.04805>



# Modele de predictive (invatare) a reprezentarilor

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## □ Modelul Word2vec

- **Skip-gram** (Mikolov et al. 2013a), **CBOW** (Mikolov et al. 2013b)
- Se invata reprezentari, numite embeddings, ca parte din procesul de predictive/generare a textului
- Se antreneaza o retea neuronală pentru prezicerea urmatorului cuvânt
- Avantaje
  - Rapid, simplu de antrenat
  - Modele gata antrente disponibile online

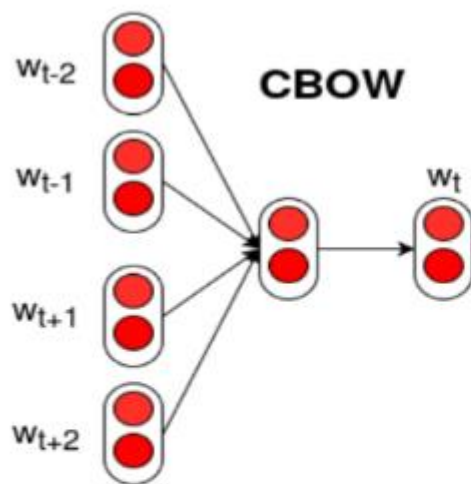
# Invatare supervizata fara etichetare manuala de date

- Text: "She rides a bike. He rides a scooter in park. My father drives a motorcycle. ..."
- Vocabular  $V = \{she, ride, bike, he, scooter, park, my, father, drive, motorcycle\}$
- Perechi (context, cuvant)

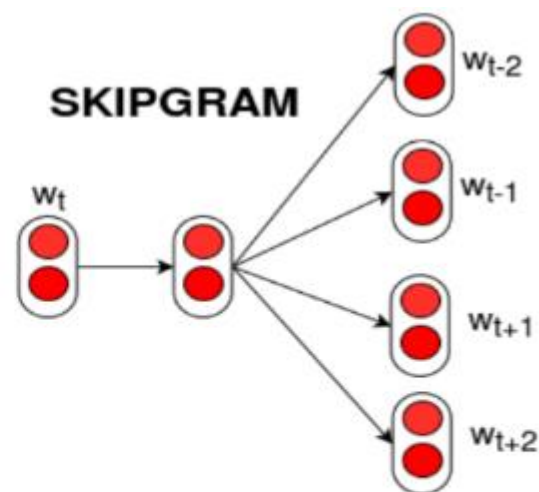
## Negative sampling

[she ride] bike	1		[she ride] he	0
[ride bike] he	1		[she ride] scooter	0
[he ride] scooter	1		[she ride] park	0
[ride scooter] park	1		[she ride] my	0
[my father] drive	1		[she ride] father	0
[father drive] motorcycle	1		[she ride] drive	0
			[ride bike] scooter	0
			[ride bike] park	0
			...	
			[father drive] she	0

# Arhitecturi



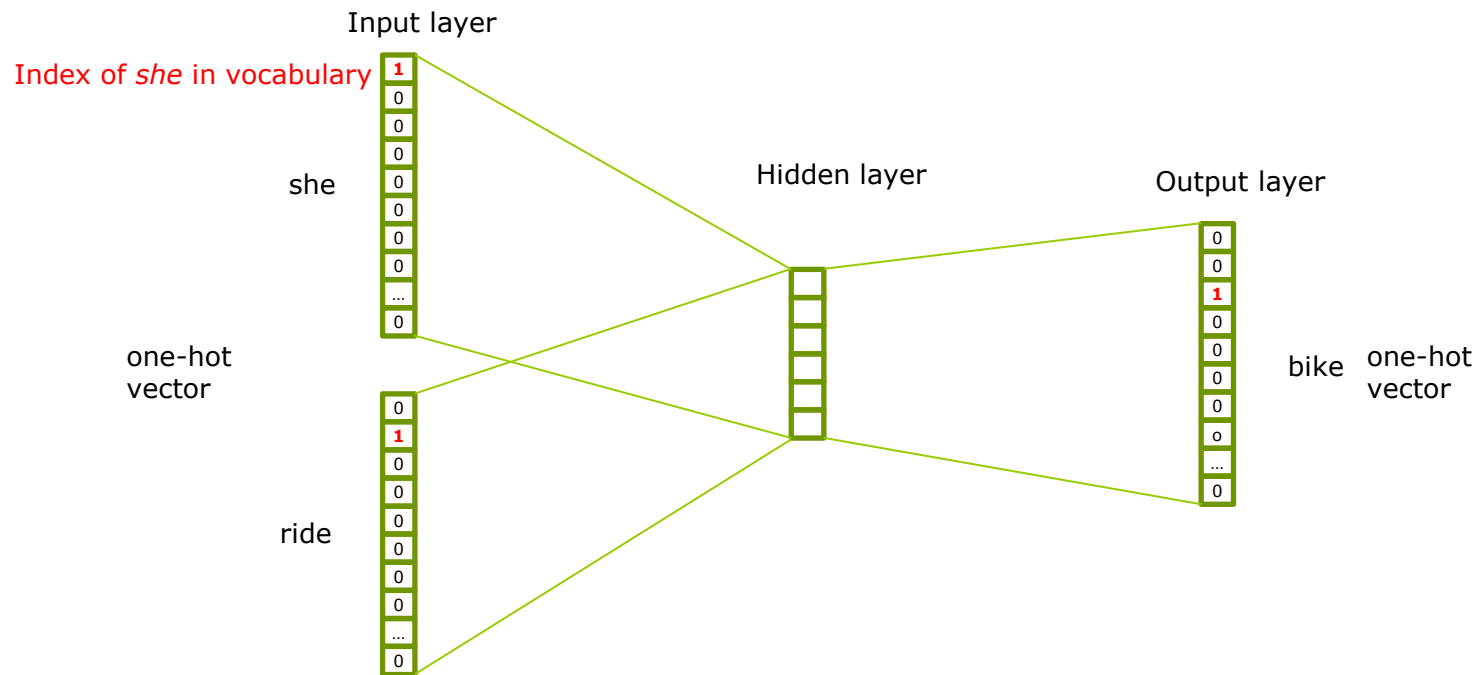
$$\frac{1}{T} \sum_{t=1}^T \sum_{-c \leq j \leq c, j \neq 0} \log p(w_t | w_{t+j})$$



$$\frac{1}{T} \sum_{t=1}^T \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j} | w_t)$$

# CBOW (Continuous Bag of Words)

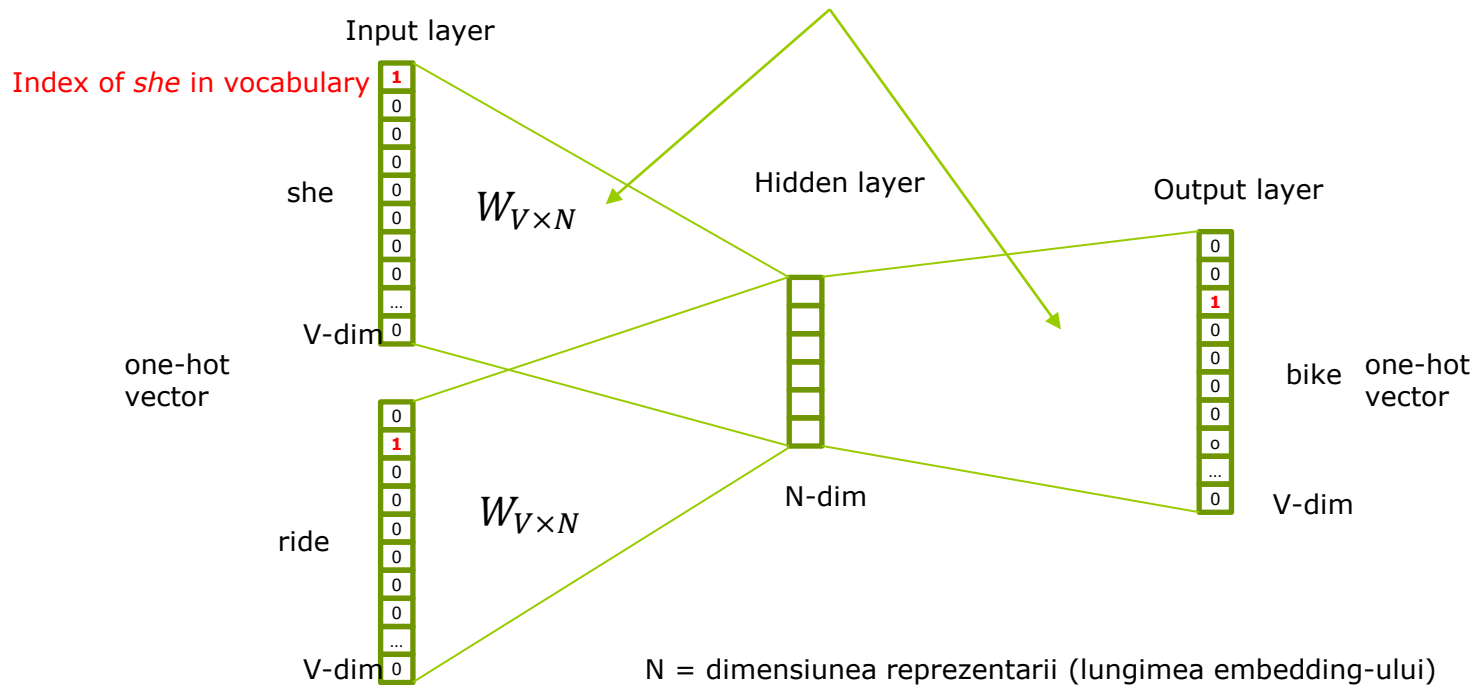
	she	ride	bike	he	scooter	park	my	father	drive	motorcycle
She	1	0	0	0	0	0	0	0	0	0
Ride	0	1	0	0	0	0	0	0	0	0
Bike	0	0	1	0	0	0	0	0	0	0



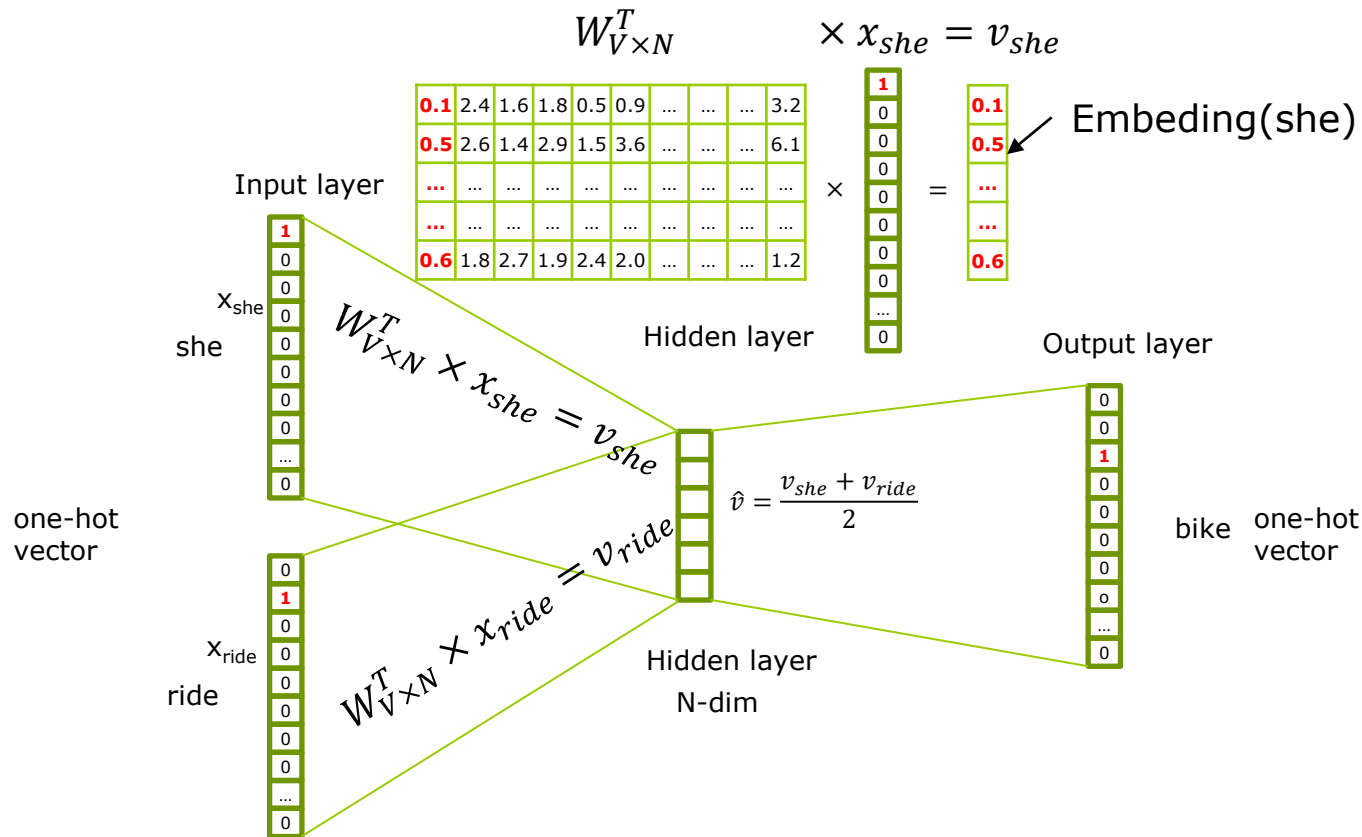
# CBOW (Continuous Bag of Words)

	she	ride	bike	he	scooter	park	my	father	drive	motorcycle
She	1	0	0	0	0	0	0	0	0	0
Ride	0	1	0	0	0	0	0	0	0	0
Bike	0	0	1	0	0	0	0	0	0	0

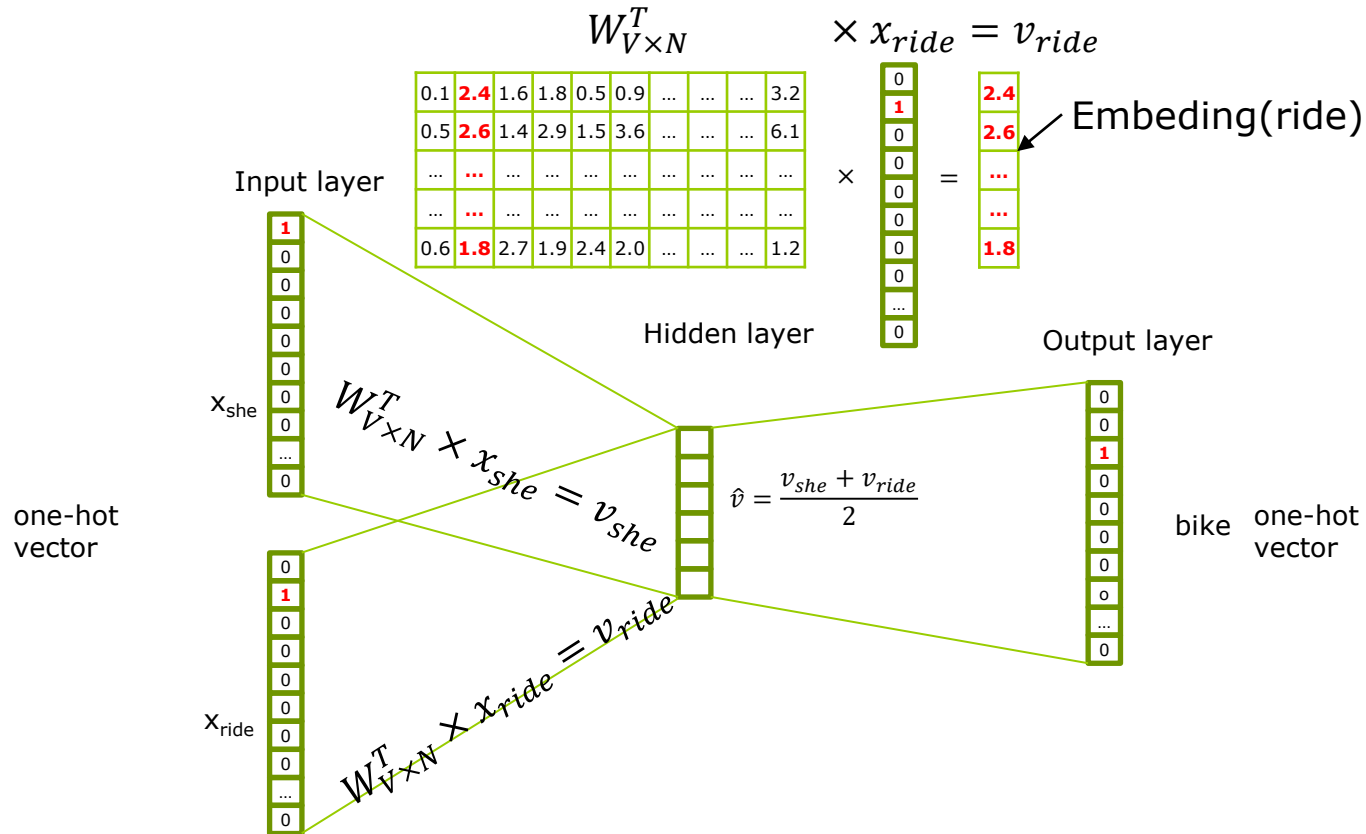
De invatat:  $W$  si  $W'$



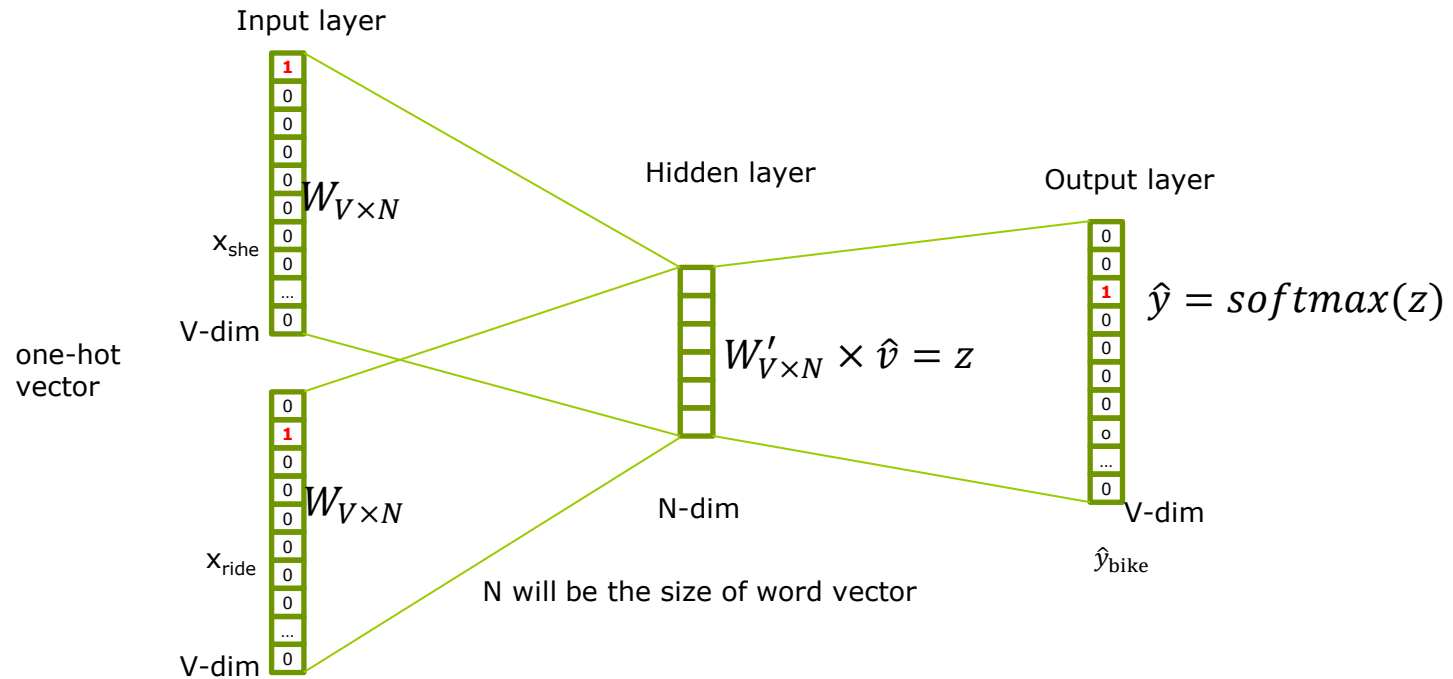
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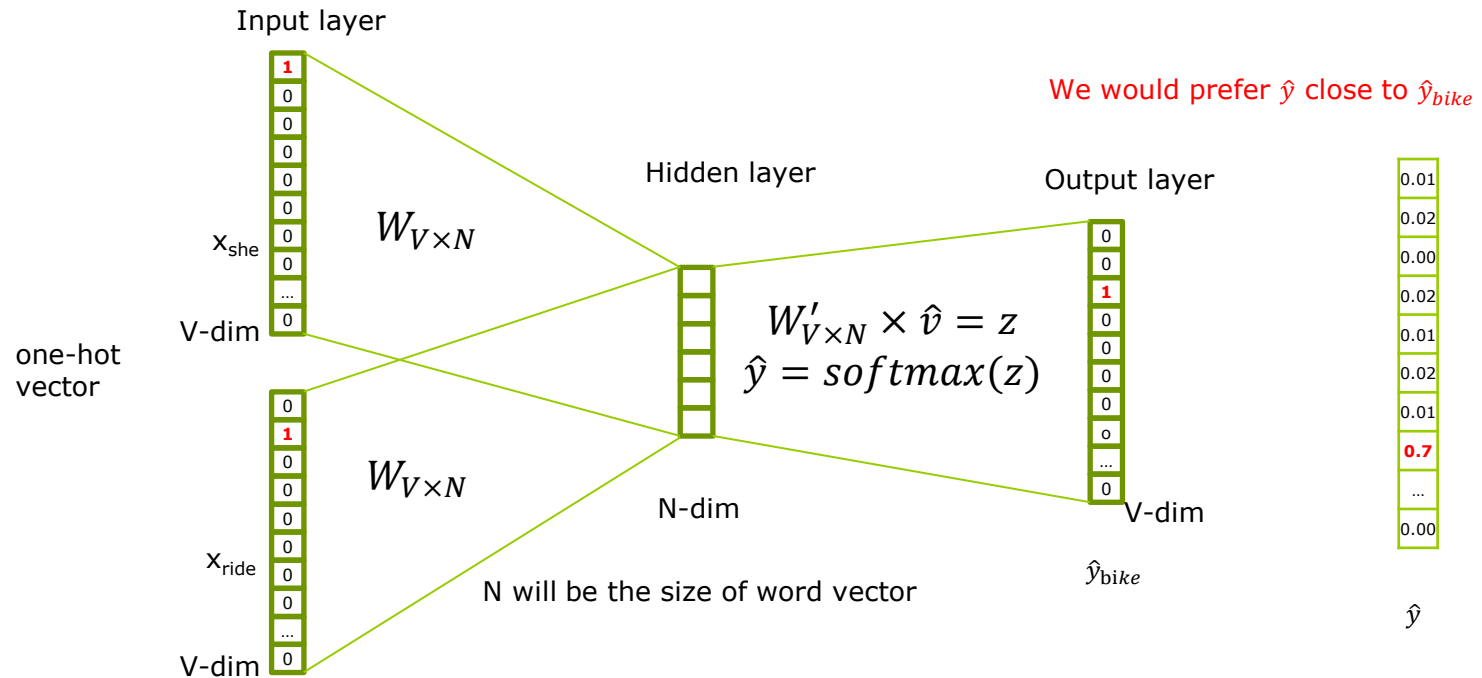


# CBOW (Continuous Bag of Words)





# CBOW (Continuous Bag of Words)



# Cursul următor

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❑ Informațiile prezentate au fost colectate din diferite surse de pe internet, precum și din cursurile de inteligență artificială ținute în anii anteriori de către:

- Conf. Dr. Mihai Oltean – [www.cs.ubbcluj.ro/~moltean](http://www.cs.ubbcluj.ro/~moltean)
- Lect. Dr. Crina Groșan – [www.cs.ubbcluj.ro/~cgrosan](http://www.cs.ubbcluj.ro/~cgrosan)
- Prof. Dr. Horia F. Pop – [www.cs.ubbcluj.ro/~hfpop](http://www.cs.ubbcluj.ro/~hfpop)
- Prof. Dr. Radu Ionescu – <https://raduionescu.herokuapp.com/>