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## **Project Falcon**

Using machine learning models to detect malwares based on processors power traces and instruction traces

#### IoT attacks

IoT devices are characterized by:

- " dedication to a single purpose or very few dedicated functions"
- " their use of nonstandard processors "
- " real-time operating systems to ensure that tasks meet timing and resource constraints "

Their are facing more and more threats: IoT malware attacks had jumped 400% from 2022 to 2023 (according a Zscaler report)

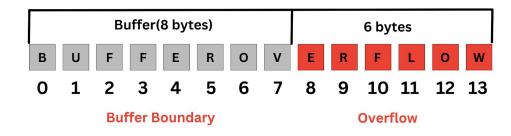
Problem: Signature detection with unique malware



#### Types of attacks on IoT



#### DLL Hijacking Attack



# Based on a processor consumption and instruction trace, detect if vulnerable functions are called



#### Ressources

We started our work by analysing three state-of-the-art papers:

Real-time instruction-level verification of remote IoT/CPS devices via side channels

Yunkai Bai · Jungmin Park · Mark Tehranipoor · Domenic Forte

Attentive transformer deep learning algorithm for intrusion detection on IoT systems using automatic Xplainable feature selection

Demóstenes Zegarra Rodríguez , Ogobuchi Daniel Okey, Siti Sarah Maidin, Ekikere Umoren Udo, João Henrique Kleinschmidt

Identification of Return-Oriented Programming Attacks Using RISC-V Instruction Trace Data Daniel F. Koranek, Scott R. Graham, Brett J. Borghetti and Wayne C. Henry



## **Data visualization**

Power trace and instruction trace

#### **Data Visualization**

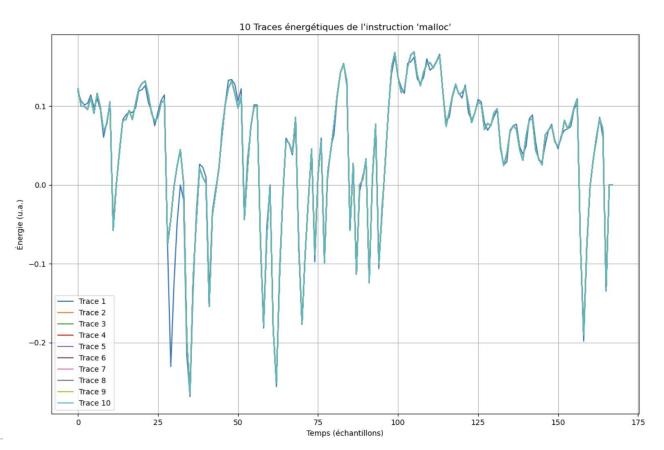
#### Our dataset:

For power traces we had:

- 11 classes of functions
- around 3500 traces per class

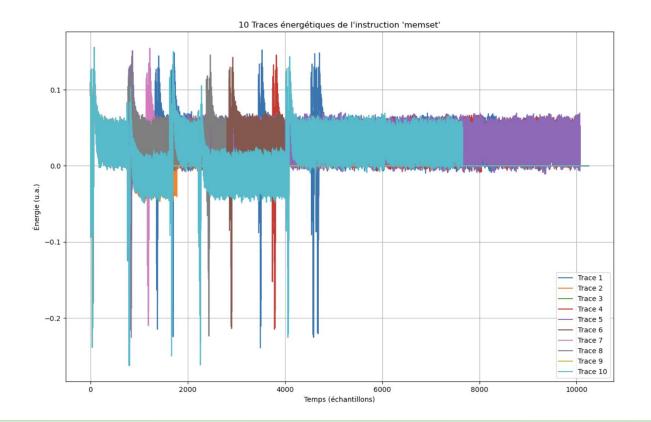


#### **Data Visualization**





#### **Data Visualization**





## How to detect such traces in an application power trace?

#### Main issues raised:

- For a given function, power traces can be longer or shorter
- It's hard to classify them with statistical methods or with classical machine learning methods (SVM, Random forests, etc..) cf I know what you do project.

#### What we need:

- A model that "looks" at patterns on the whole signal
- A model that understand the global context of those patterns





#### The transformer model originally designed for natural language allow us to:

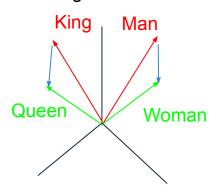
- capture global patterns
- handle variable length sequences
- highly parallelizable architecture



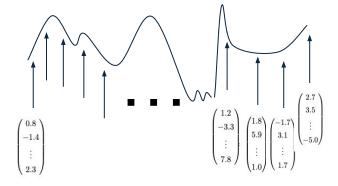
#### Values of the power trace are like words in a sentence

Each word of the sentence is encoded as high dimension vector (12,288 dimension on GPT-3)

Directions have semantic meanings



We do the same thing for each value of the trace (dimension 128)





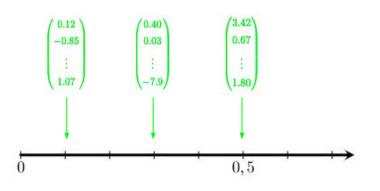
- 2.7: normalized power
- 3.5: similarity to a peak in calloc
- .
- -5.0: similarity to a decrease in free

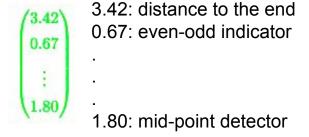


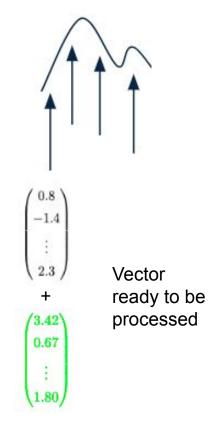
#### Meaning is encoded

When processing a sentence/trace, we also need the position of the word/value to be encoded

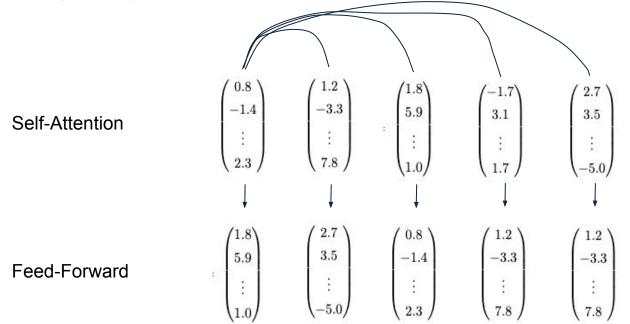
We encode the positions with high-dimension vectors (128 also)







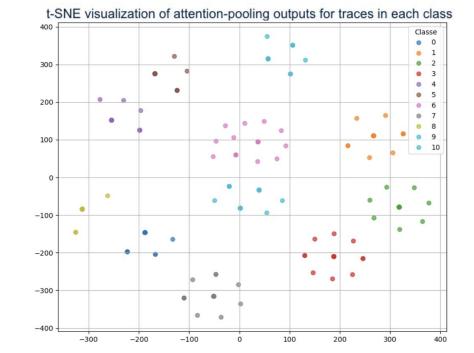
Vectors go through encoders blocks



**4**x

#### Two last steps:

- Attention pooling: gives a unique vector for the trace capturing the most relevant information
- Classifier: associate logits to each class of function based on this unique vector



unique vector 
$$\begin{pmatrix} 2.7\\ 3.5\\ \vdots\\ -5.0 \end{pmatrix}$$
  $classifier$  sprintf : 0.5 memset: -4 memcopy: 9 strncat: 3.4

. . .

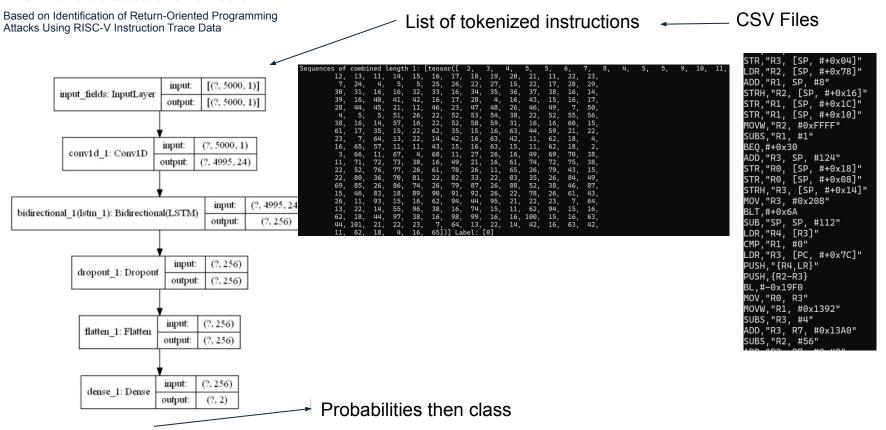
probability — class prediction

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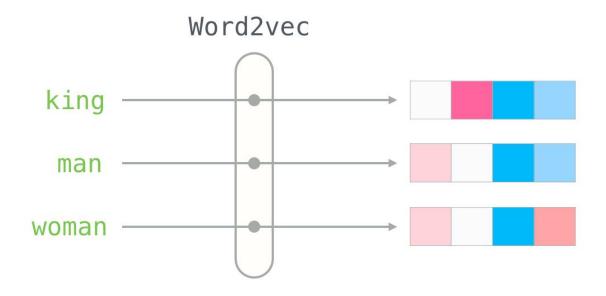
## The LSTM model

#### From the data to the function





#### The model inside the model

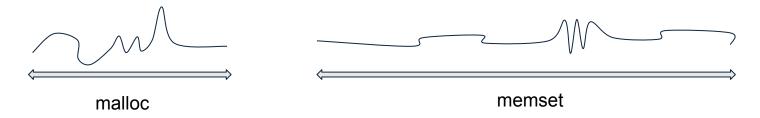




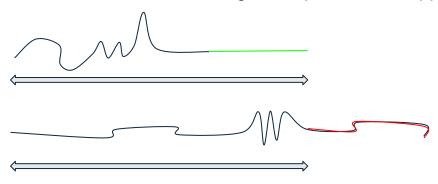
## **Our results on function traces**

#### Problems we had

#### Model recognizes functions only with their length



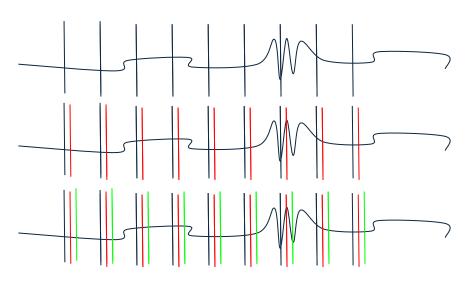
So we chose a standard length and padded or cropped the traces



We lost a big part of the dataset, especially on long traces, the model couldn't learn properly

#### Problems we had

We transformed the dataset in fixed length windows of traces

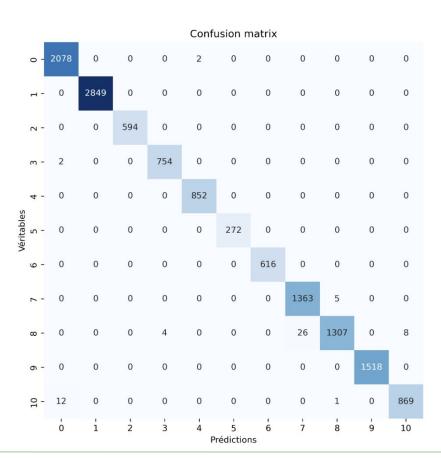


- Step-size of 1
- After different tries we chose windows of 100 timesteps
- Gave up on detecting the smallest function (free: 34 timesteps)

Unbalanced dataset: 1 malloc trace = 2 windows vs 1 snprintf trace = 250 windows We chose a fixed number of window per class
We train the model to classify windows

#### **Confusion matrix**

acc = 99.98%



#### **Dataset composition**

Fonction	Entraînement	Test
calloc	2160	540
free	2160	540
malloc	2160	540
темсору	2160	540
memset	2160	540
memmove	2160	540
snprintf	2160	540
sprintf	2160	540
strcpy	2160	540
strcat	2160	540
strncpy	2160	540
strncat	2160	540



#### Results

#### Confusion matrix - 12 fonctions

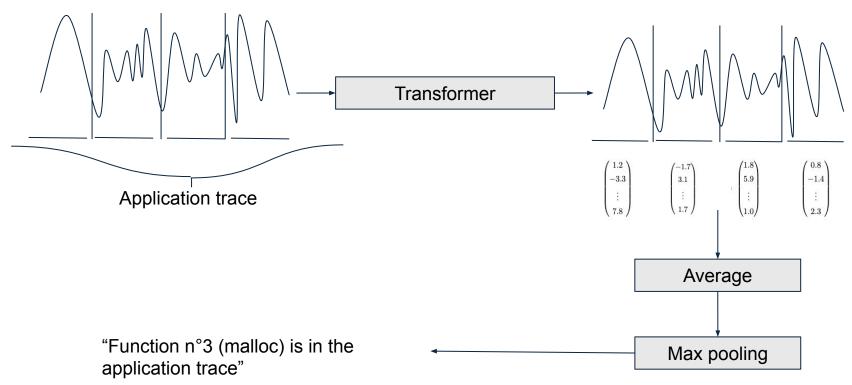
True label	Predicted label											
	calloc	free	malloc	memcopy	memmove	memset	snprintf	sprintf	strcat	strcpy	strncat	strncpy
calloc		0	0		0	0	0	0		0	0	0
free	0		0							0		
malloc	0	0	540	0	0	0	0	0		0	0	0
тетсору	0	0	0		0	0	0	0	0	0	0	0
memmove	0	0	0		540	0	0	0		0	0	0
memset	39	0	0	0	0	501	0	0	0	0	0	0
snprintf	0	0	0	0	3	0	537	0	0	0	0	0
sprintf	0	0	0		0	0	0		0	0	0	0
strcat	0	0	0	0	0	0	0	0	539	1	0	0
strcpy	0	0	0	0	0	0	0	0	0	540	0	0
strncat	0	0	0		0	0	0	0	0	0		0
strncpy	0	0	0		0	0	0	0	0	0	0	



## **Extension to application traces**

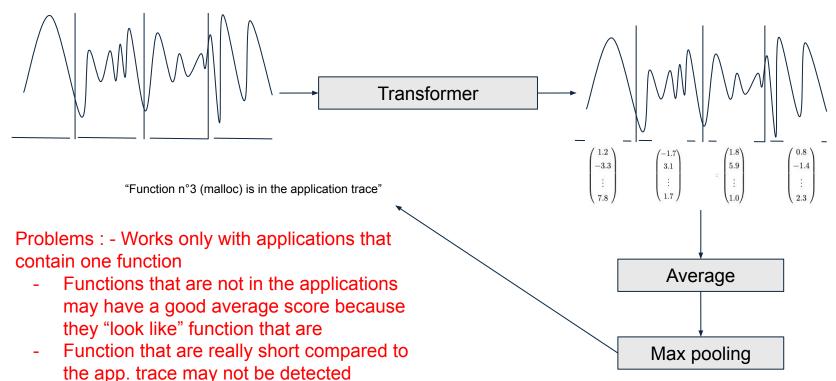
Goal: We want the model to recognize functions in application power traces

First method: Choose the prediction with the best average score



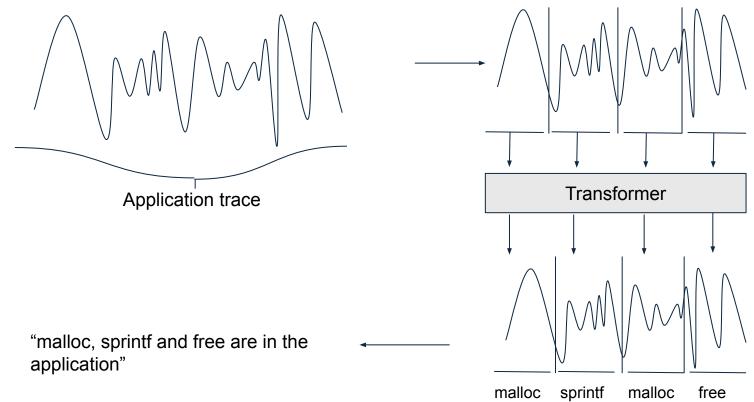


First method: Choose the prediction with best average score





Second method: Make a prediction for each window independently





Results for application sprcat (sprintf and strcat) with Method 1

```
Trace 97: fonction prédite = 'strncat'
Trace 97: fonction prédite = 'strncat'
Trace 97: fonction prédite = 'sprintf'
Trace 97: fonction prédite = 'strncat'
```

Prediction for one window

#### **Prediction on applications**

Applicati on	1	2	3	4	5	6	7	8
Prédictio n								



#### **Final results**

#### For power traces:

- Function power traces classification : almost 100%
- Function power traces identification in application traces: a few good results

#### For instruction traces:

- With only the identified function : almost 100%
- In a real context: can predict some functions and when there is nothing



## Limitation of our work

#### **Limitations**

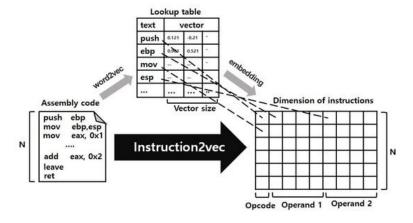
- Training time can be long
- Creation of the vocabulary is delegated to a model made for human language
- Generalization is harder due to noise, shift and not having the knowledge of start and end points
- Defining the window seems easy during training but harder in reality



#### **Next steps**

Reviewing the window and making sure each sequences has already been seen

Implementing a new tokenization, more efficient based on paper : "Instruction2vec: Efficient Preprocessor of Assembly Code to Detect Software Weakness with CNN"







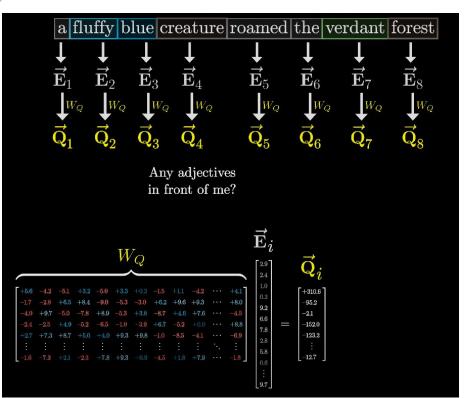


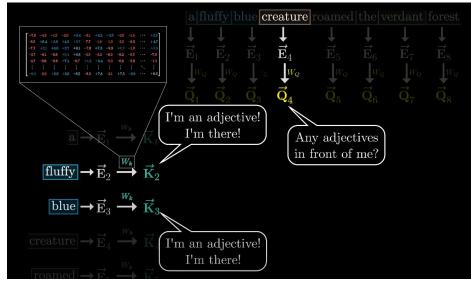
## Thank you for your attention

Timothée Léveillé Auguste Célérier

## **Annexes**

#### **Query and key vectors**



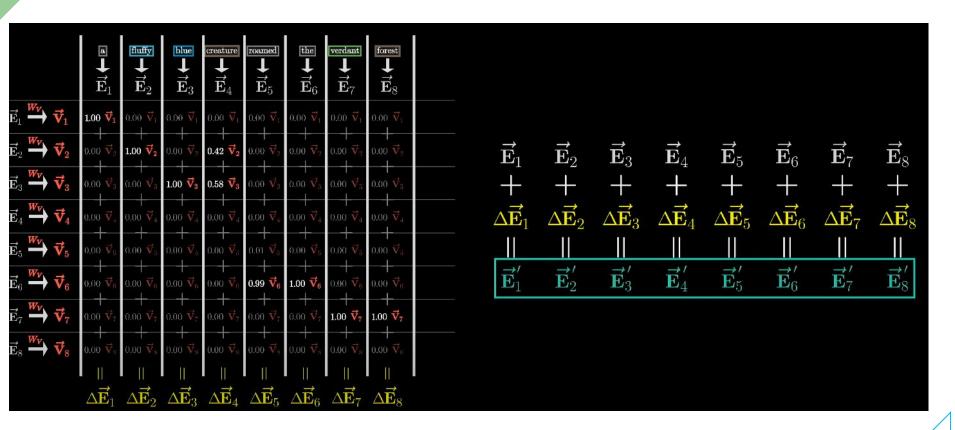


#### **Query and key vectors**

	$egin{array}{c} igotharpoonup \ddot{\mathbf{E}}_1 \ oldsymbol{\ddot{\mathbf{E}}}_1 \ oldsymbol{\ddot{\mathbf{Q}}}_1 \end{array}$	$egin{array}{c}  ext{fluffy} \  extbf{L} \  extbf{E}_2 \  extbf{L} \  extbf{Q}_2 \  ext{Q}_2 \end{array}$	$\begin{array}{c c} \mathbf{\overline{blue}} \\ \mathbf{\overline{E}}_3 \\ \mathbf{\overline{Q}}_3 \end{array}$	$egin{array}{c}  ext{creature} \  extbf{E}_4 \  extbf{Q}_4 \  ext{Q}_4 \end{array}$	$egin{array}{c}  ext{roamed} \  extbf{F}_5 \  extbf{Q}_5 \  ext{Q}_5 \ \end{array}$	$ec{\mathbf{E}}_{6}$ $ec{\mathbf{Q}}_{6}$	$\begin{array}{c} \mathbf{verdant} \\ \mathbf{{E}}_{7} \\ \mathbf{{Q}}_{7} \end{array}$	$\begin{matrix} \mathbf{forest} \\ \mathbf{\dot{E}}_8 \\ \mathbf{\ddot{Q}}_8 \end{matrix}$	
$\mathbf{a} \!  o \! \vec{\mathbf{E}}_1 \overset{W_k}{\longrightarrow} \vec{\mathbf{K}}_1$	$\vec{\mathbf{K}}_{1}ullet \vec{\mathbf{Q}}_{1}$	$ec{\mathbf{K}}_1ullet ec{\mathbf{Q}}_2$	$\vec{\mathbf{K}}_1 ullet \vec{\mathbf{Q}}_3$	$ec{\mathbf{K}}_1ullet ec{\mathbf{Q}}_4$	$\vec{\mathbf{K}}_1$ $\mathbf{Q}_5$	$ec{\mathbf{K}}_1ullet ec{\mathbf{Q}}_6$	$\vec{\mathbf{K}}_1 \cdot \vec{\mathbf{Q}}_7$	$\vec{\mathbf{K}}_1 \mathbf{O} \vec{\mathbf{Q}}_8$	
$\boxed{\text{fluffy}} \rightarrow \vec{\mathbf{E}}_2 \stackrel{W_k}{\longrightarrow} \vec{\mathbf{K}}_2$	$\vec{\mathbf{K}}_{2}$ $\mathbf{\vec{Q}}_{1}$	$ec{\mathbf{K}}_2 oldsymbol{\mathbf{Q}}_2$	$ec{\mathbf{K}}_2$ O $ec{\mathbf{Q}}_3$	$\vec{R}_2 \cdot \vec{Q}_1$	$ec{\mathbf{K}}_2 ullet ec{\mathbf{Q}}_5$	$ec{\mathbf{K}}_2$ $oldsymbol{ar{\mathbf{Q}}}_6$	$ec{\mathbf{K}}_2 \cdot ec{\mathbf{Q}}_7$	$ec{\mathbf{K}}_2$ $ec{\mathbf{Q}}_8$	
	$\vec{\mathbf{K}}_3 \mathbf{Q}_1$	$\vec{\mathbf{K}}_3$ $\mathbf{Q}_2$	$\vec{\mathbf{K}}_3 \cdot \vec{\mathbf{Q}}_3$	$\vec{K}_3 \cdot \vec{Q}_1$	$\vec{\mathbf{K}}_3 ullet \vec{\mathbf{Q}}_5$	$\vec{\mathbf{K}}_3 ullet \vec{\mathbf{Q}}_6$	$\vec{\mathbf{K}}_3 \mathbf{\circ} \vec{\mathbf{Q}}_7$	$\vec{\mathbf{K}}_3$ $\mathbf{Q}_8$	
$\boxed{\text{creature}} \rightarrow \vec{\mathbf{E}}_4 \stackrel{W_k}{\longrightarrow} \vec{\mathbf{K}}_4$	$\vec{\mathbf{K}}_{4}^{\bullet}\cdot\vec{\mathbf{Q}}_{1}$	$ec{\mathbf{K}}_{ec{q}} oldsymbol{ec{Q}}_2$	$ec{\mathbf{K}}_4$ $\mathbf{Q}_3$	$\vec{\mathbf{K}}_4 \cdot \vec{\mathbf{Q}}_4$	$\vec{\mathbf{K}}_4 ullet \vec{\mathbf{Q}}_5$	$\vec{\mathbf{K}} lackbox{0} \vec{\mathbf{Q}}_6$	$\vec{\mathbf{K}}_{4}^{\bullet}\cdot\vec{\mathbf{Q}}_{7}$	$\vec{\mathbf{K}}_4ullet \vec{\mathbf{Q}}_8$	
$\boxed{\text{roamed}} \to \vec{\mathbf{E}}_5 \stackrel{W_k}{\longrightarrow} \vec{\mathbf{K}}_5$	$\vec{\mathbf{K}}_{5}$ • $\vec{\mathbf{Q}}_{1}$	$ec{\mathbf{K}}_{5}\mathbf{O}ec{\mathbf{Q}}_{2}$	$ec{\mathbf{K}}_{5} \mathbf{\circ} ec{\mathbf{Q}}_{3}$	$ec{\mathbf{K}}_{\delta}\mathbf{C}ec{\mathbf{Q}}_{4}$	$\vec{\mathbf{K}}_5 ullet \vec{\mathbf{Q}}_5$	$\vec{\mathbf{K}}_{\delta}$ $\mathbf{Q}$ $\vec{\mathbf{Q}}_{\delta}$	$\vec{\mathbf{K}}_5 \! \cdot \! \vec{\mathbf{Q}}_7$	$ec{\mathbf{K}}_{5}$ O $ec{\mathbf{Q}}_{8}$	
$ \underbrace{\text{the}} \to \vec{\mathbf{E}}_6 \overset{w_k}{\longrightarrow} \vec{\mathbf{K}}_6 $	$\vec{\mathbf{K}}_{6}$ $\mathbf{\vec{Q}}_{1}$	$ec{\mathbf{K}}_6 \circ ec{\mathbf{Q}}_2$	$ec{\mathbf{K}}_6 \circ ec{\mathbf{Q}}_3$	$ec{\mathbf{K}}_6$ O $ec{\mathbf{Q}}_4$	$\vec{\mathbf{K}}_6 ullet \vec{\mathbf{Q}}_5$	$ec{\mathbf{K}}_6$ $\mathbf{Q}_6$	$\vec{\mathrm{K}}_6$ O $\vec{\mathrm{Q}}_7$	$ec{\mathbf{K}}_6 \cdot ec{\mathbf{Q}}_8$	
$ \overrightarrow{\text{verdant}} \to \overrightarrow{\mathbf{E}}_7 \stackrel{w_k}{\longrightarrow} \overrightarrow{\mathbf{K}}_7 $	$\vec{\mathbf{K}}_{7}^{oldsymbol{\circ}} \vec{\mathbf{Q}}_{1}$	$ec{\mathbf{K}}_{7}$ $\mathbf{Q}_{2}$	$\vec{\mathbf{K}}_7 \circ \vec{\mathbf{Q}}_3$	$\vec{\mathrm{K}}_7 \cdot \vec{\mathrm{Q}}_4$	$\vec{\mathbf{K}}_7ullet \vec{\mathbf{Q}}_5$	$\vec{\mathbf{K}}_7 ullet \vec{\mathbf{Q}}_6$	ĸ̄ <sub>7</sub> ⊙Q̄ <sub>7</sub>	$\mathbf{K}_7 \cdot \mathbf{\bar{Q}}_8$	
$\boxed{\text{forest} \rightarrow \vec{\mathbf{E}}_8 \stackrel{W_k}{\longrightarrow} \vec{\mathbf{K}}_8}$	$\vec{\mathbf{K}}_{s}$ $\mathbf{\vec{Q}}_{1}$	$\vec{\mathbf{K}}_8 ullet \vec{\mathbf{Q}}_2$	$\vec{\mathbf{K}}_8 * \vec{\mathbf{Q}}_3$	$\vec{\mathbf{K}}_{8}ullet \vec{\mathbf{Q}}_{4}$	$\vec{\mathbf{K}}_8$ • $\vec{\mathbf{Q}}_5$	$\vec{\mathbf{K}}_8$ $\bullet$ $\vec{\mathbf{Q}}_6$	$\vec{\mathbf{K}}_{8}$ $\mathbf{Q}_{7}$	$\vec{\mathbf{K}}_8$ • $\vec{\mathbf{Q}}_8$	



#### Value vectors and update of embeddings





#### Attention pooling and classifier

#### **Attention pooling**

For each vector we calculate an importance score

We softmax these scores

We multiply each vector by its softmaxed score and we sum

#### Classifier

z : output of attention pooling

W: matrice of trained weights to classify

b: trained bias

logits = Wz + b