# Fundamentals of Deep Learning

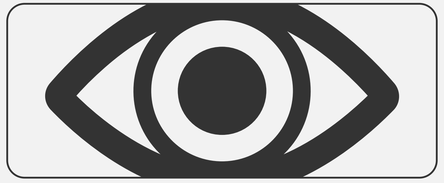
Part 6: Advanced Architectures

# Agenda

- Part 1:  An Introduction to Deep Learning
- Part 2: How a Neural Network Trains
- Part 3: Convolutional Neural Networks
- Part 4: Data Augmentation and Deployment
- Part 5: Pre-Trained Models
- Part 6: Advanced Architectures

# Moving Forward

# Fields of AI

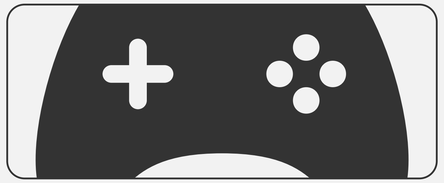


## Computer Vision

- Optometry

## Natural Language Processing

- Linguistics



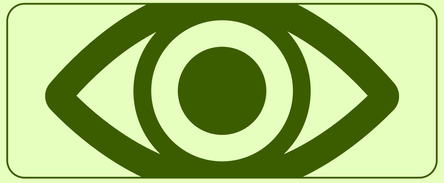
## Reinforcement Learning

- Game Theory
- Psychology

## Anomaly Detection

- Security
- Medicine

# Fields of AI



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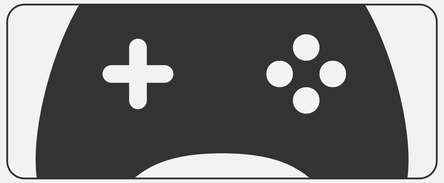

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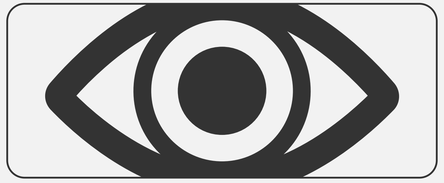

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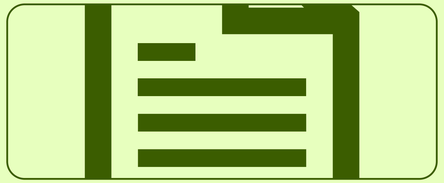

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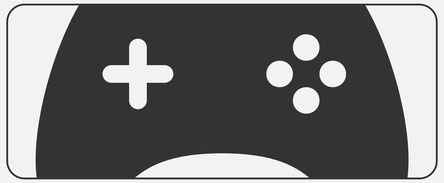


## Reinforcement Learning

- Game Theory
- Psychology

## Anomaly Detection

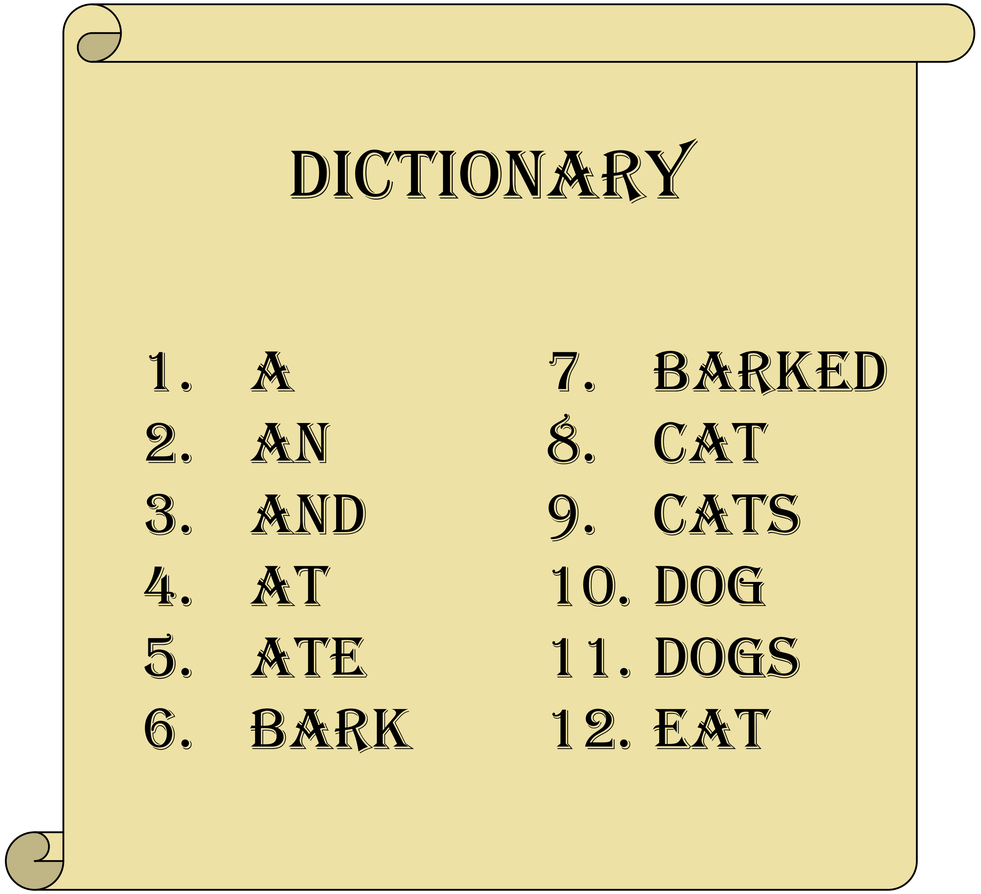
- Security
- Medicine

# Natural Language Processing

# From Words to Numbers

"A dog barked at a cat."

[1, 10, 7, 4, 1, 8]



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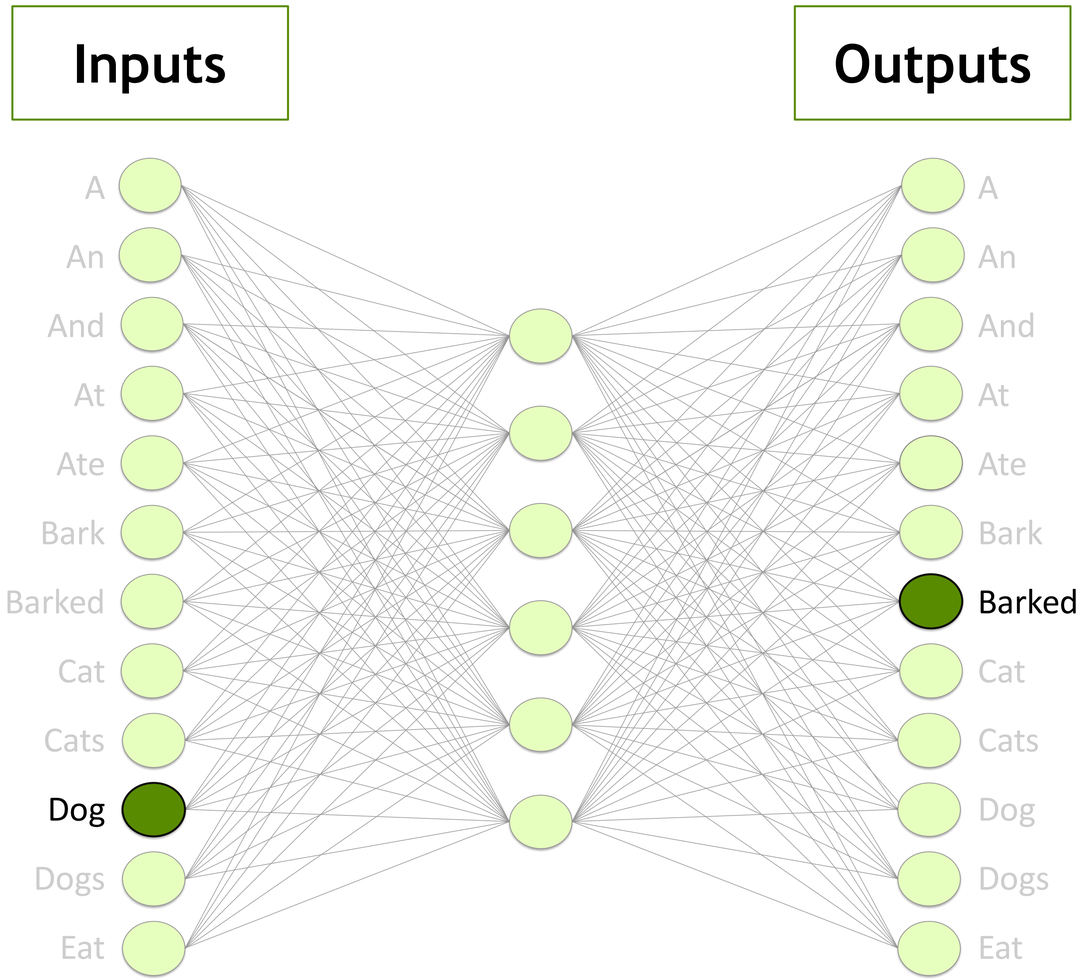
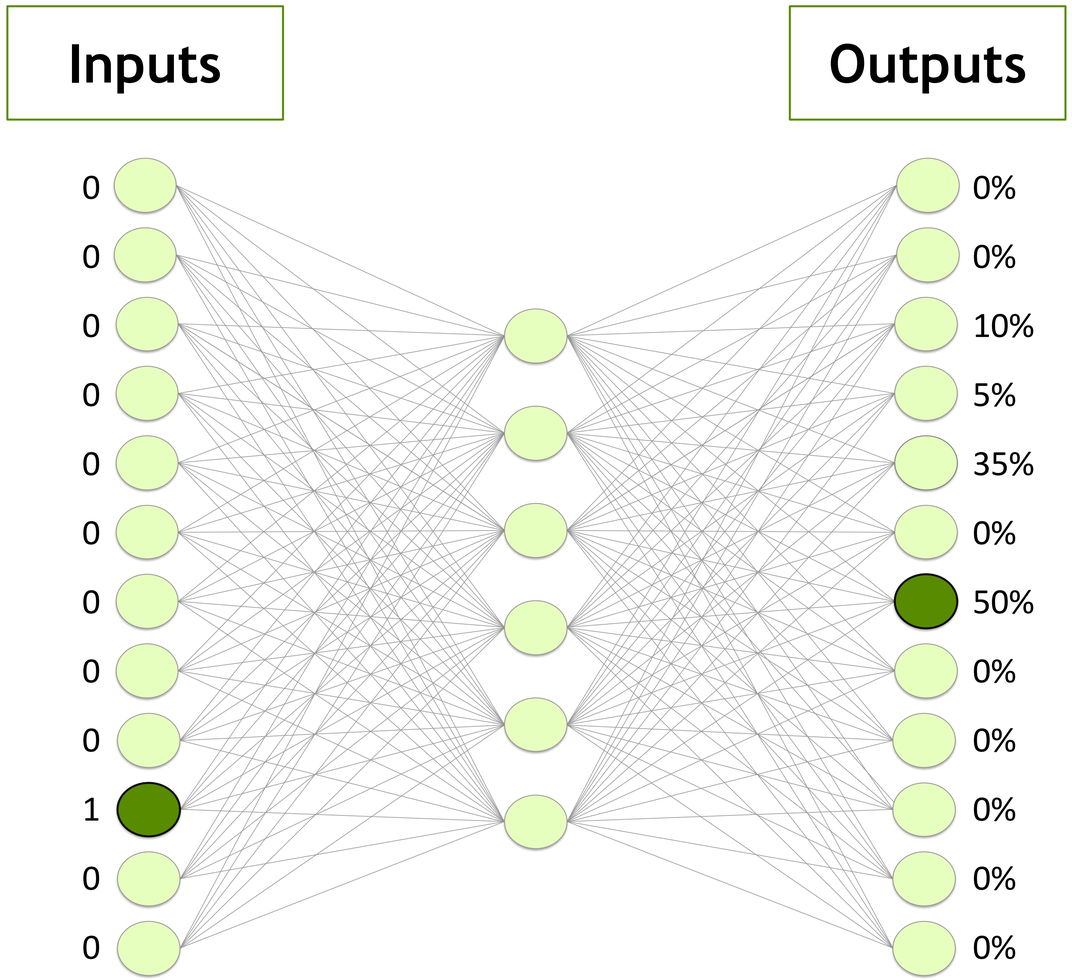
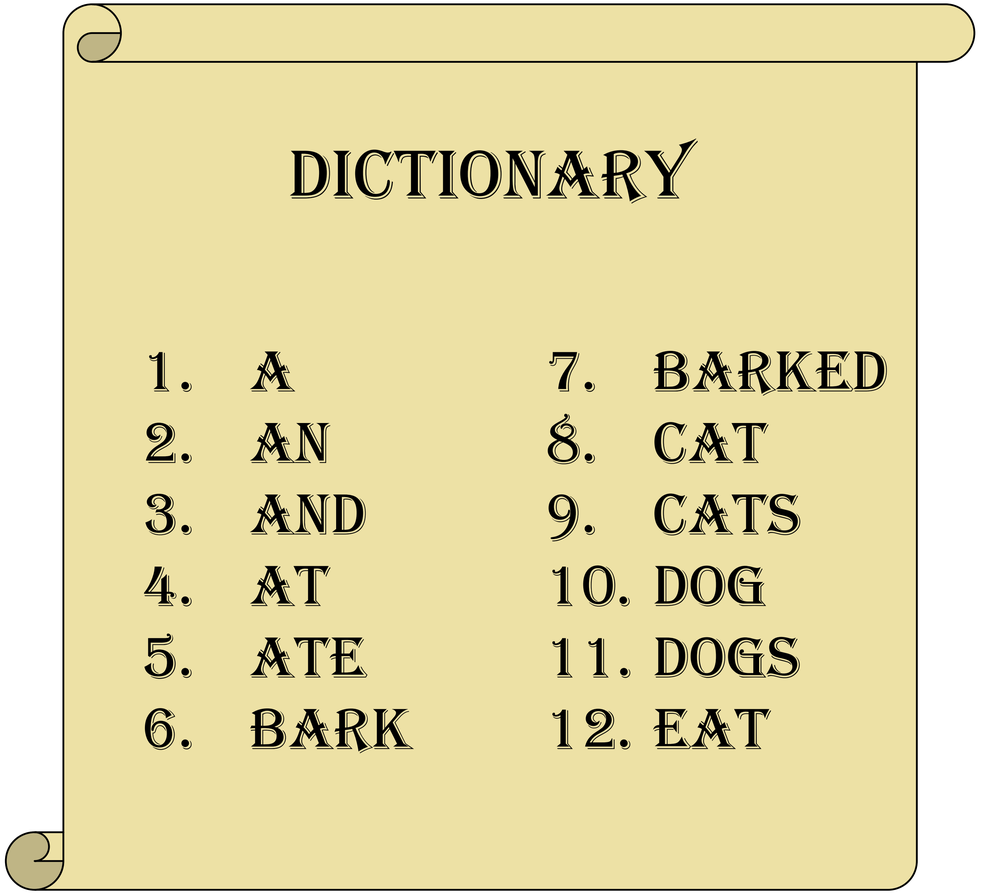



## DICTIONARY

1. A
2. AN
3. AND
4. AT
5. ATE
6. BARK
7. BARKED
8. CAT
9. CATS
10. DOG
11. DOGS
12. EAT

# From Words to Numbers



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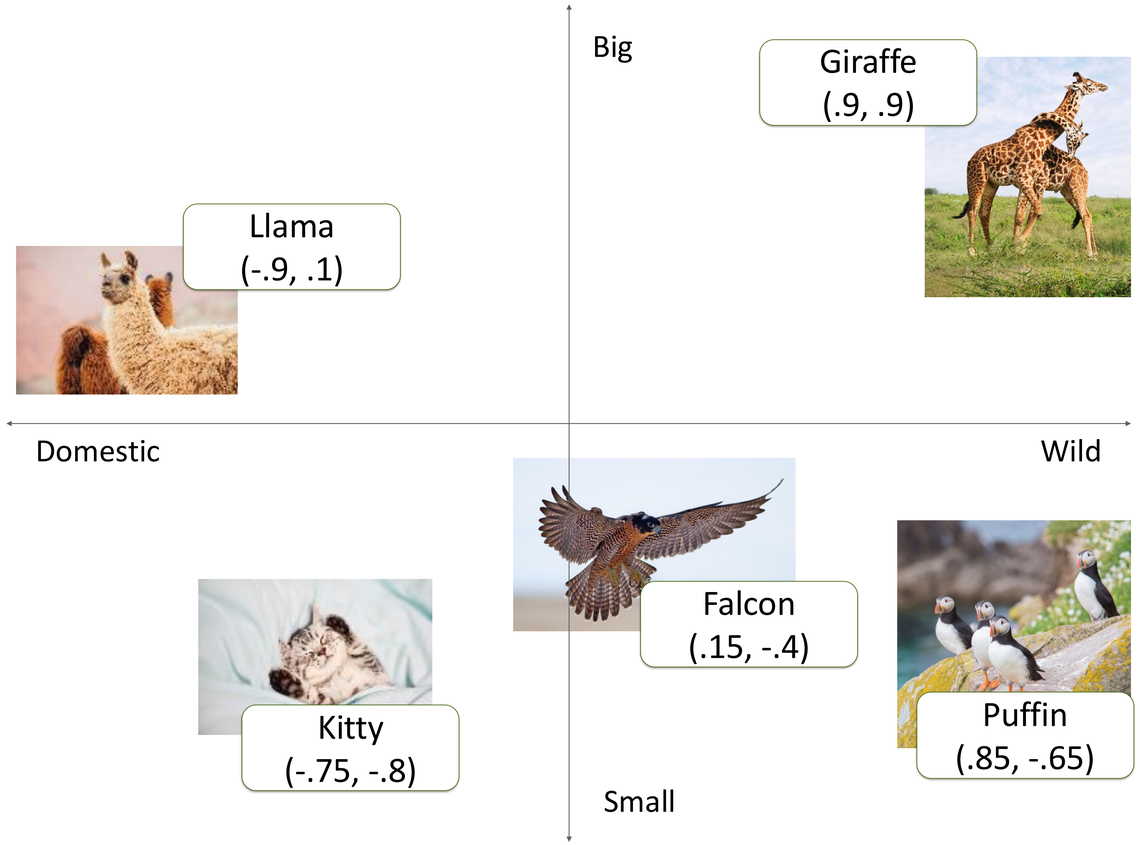
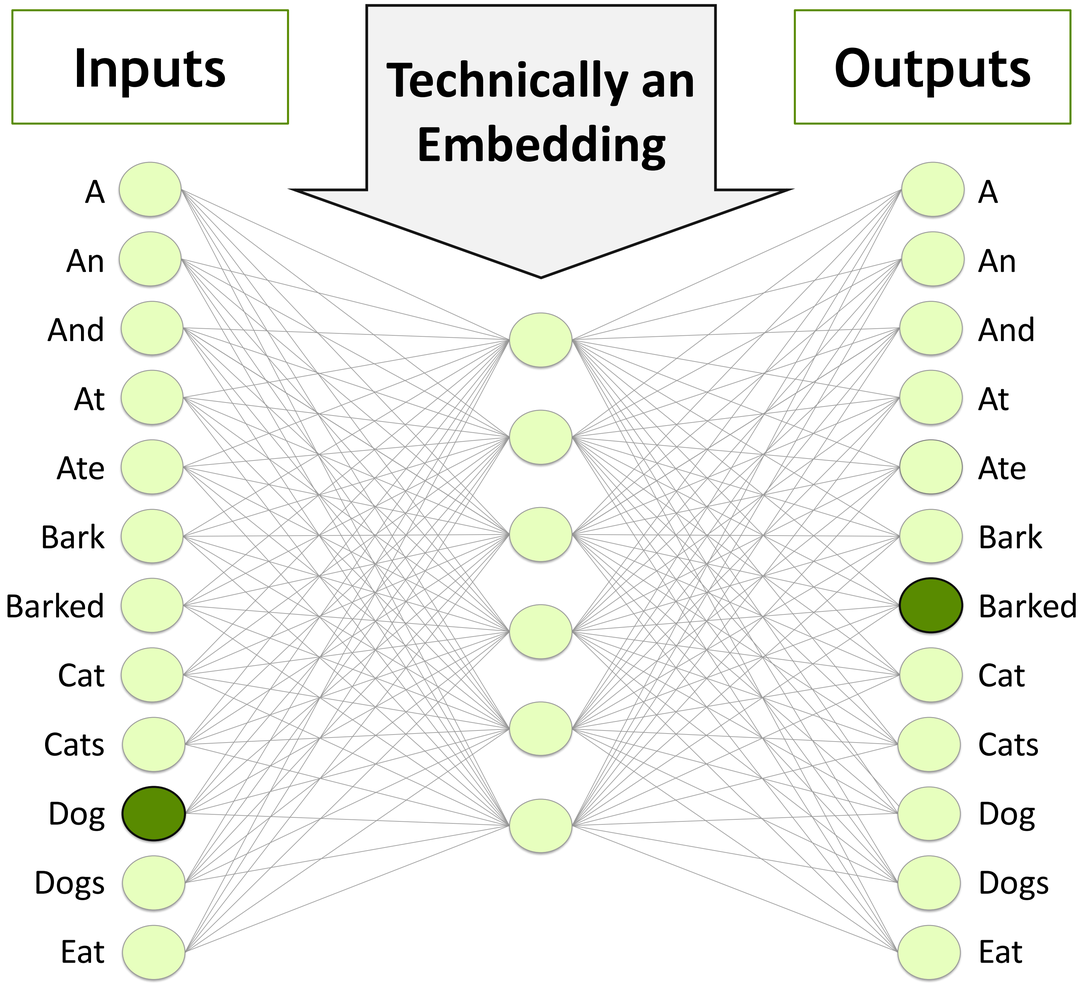



## BIGGER DICTIONARY

| | | | | | |
|---|---|---|---|---|---|
| 1. | A | 33. | BARKED | 65. | EATEN |
| 2. | AN | 34. | CAT | 66. | A |
| 3. | AND | 35. | CATS | 67. | AN |
| 4. | AT | 36. | DOG | 68. | AND |
| 5. | ATE | 37. | DOGS | 69. | AT |
| 6. | BARK | 38. | EAT | 70. | ATE |
| 7. | BARKED | 39. | EATEN | 71. | BARK |
| 8. | CAT | 40. | A | 72. | BARKED |
| 9. | CATS | 41. | AN | 73. | CAT |
| 10. | DOG | 42. | AND | 74. | CATS |
| 11. | DOGS | 43. | AT | 75. | DOG |
| 12. | EAT | 44. | ATE | 76. | DOGS |
| 13. | EATEN | 45. | BARK | 77. | EAT |
| 14. | A | 46. | BARKED | 78. | EATEN |
| 15. | AN | 47. | CAT | 79. | ... |
| 16. | AND | 48. | CATS | 80. | ... |
| 17. | AT | 49. | DOG | 81. | ... |
| 18. | ATE | 50. | DOGS | 82. | ... |
| 19. | BARK | 51. | EAT | | |
| 20. | BARKED | 52. | EATEN | | |
| 21. | CAT | 53. | A | | |
| 22. | CATS | 54. | AN | | |
| 23. | DOG | 55. | AND | | |
| 24. | DOGS | 56. | AT | | |
| 25. | EAT | 57. | ATE | | |
| 26. | EATEN | 58. | BARK | | |
| 27. | A | 59. | BARKED | | |
| 28. | AN | 60. | CAT | | |
| 29. | AND | 61. | CATS | | |
| 30. | AT | 62. | DOG | | |
| 31. | ATE | 63. | DOGS | | |
| 32. | BARK | 64. | EAT | | |

# From Words to Numbers

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| 6. | BARK | 38. | EAT | 70. | ATE |
| 7. | BARKED | 39. | EATEN | 71. | BARK |
| 8. | CAT | 40. | A | 72. | BARKED |
| 9. | CATS | 41. | AN | 73. | CAT |
| 10. | DOG | 42. | AND | 74. | CATS |
| 11. | DOGS | 43. | AT | 75. | DOG |
| 12. | EAT | 44. | ATE | 76. | DOGS |
| 13. | EATEN | 45. | BARK | 77. | EAT |
| 14. | A | 46. | BARKED | 78. | EATEN |
| 15. | AN | 47. | CAT | 79. | ... |
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| 21. | CAT | 53. | A | | |
| 22. | CATS | 54. | AN | | |
| 23. | DOG | 55. | AND | | |
| 24. | DOGS | 56. | AT | | |
| 25. | EAT | 57. | ATE | | |
| 26. | EATEN | 58. | BARK | | |
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| 30. | AT | 62. | DOG | | |
| 31. | ATE | 63. | DOGS | | |
| 32. | BARK | 64. | EAT | | |

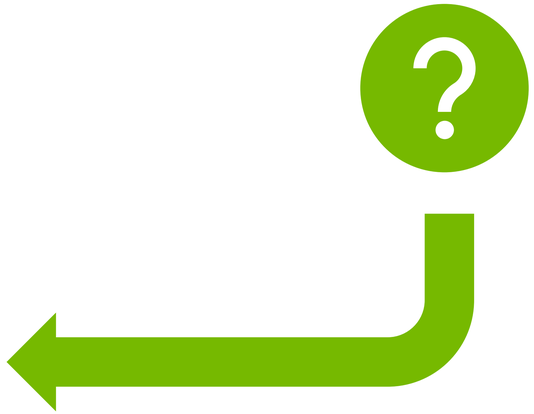
# Attention

# Sentence Prediction

I am the very model of a modern Major-Gineral,
I've information vegetable, animal, and mineral,

...

I'm very good at integral and differential calculus;
I know the scientific names of beings animalculous:
In short, in matters vegetable, animal, and mineral,
I am the very model of a m



~ Major-General Stanley

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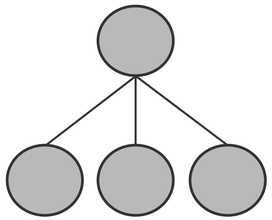
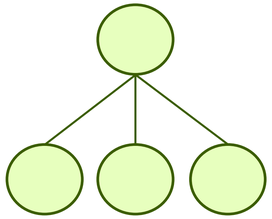




| I |
| --- |
| am |
| the |
| very |
| model |

5 x 3

Q

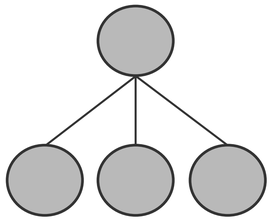
Query

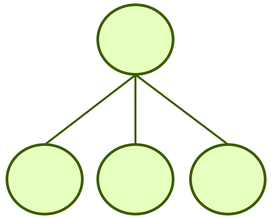
5 x 3

K

Key

# Attention





| | | | | | | |
|---|---|---|---|---|---|---|
| I | | | | | | |
| am | | | | | | |
| the | | | | | | |
| very | | | | | | |
| model | | | | | | |

5 x 3

Q

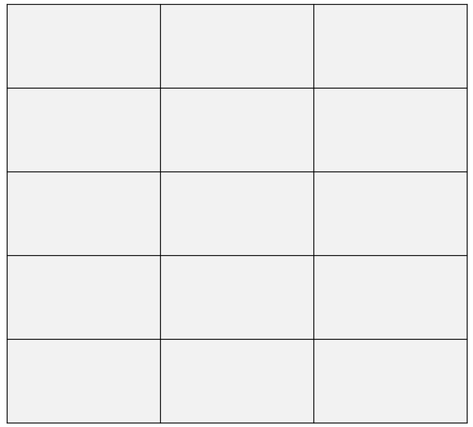
Query

5 x 3

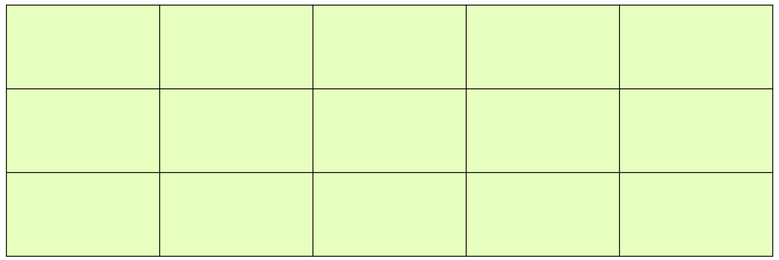
K

Key

# Attention

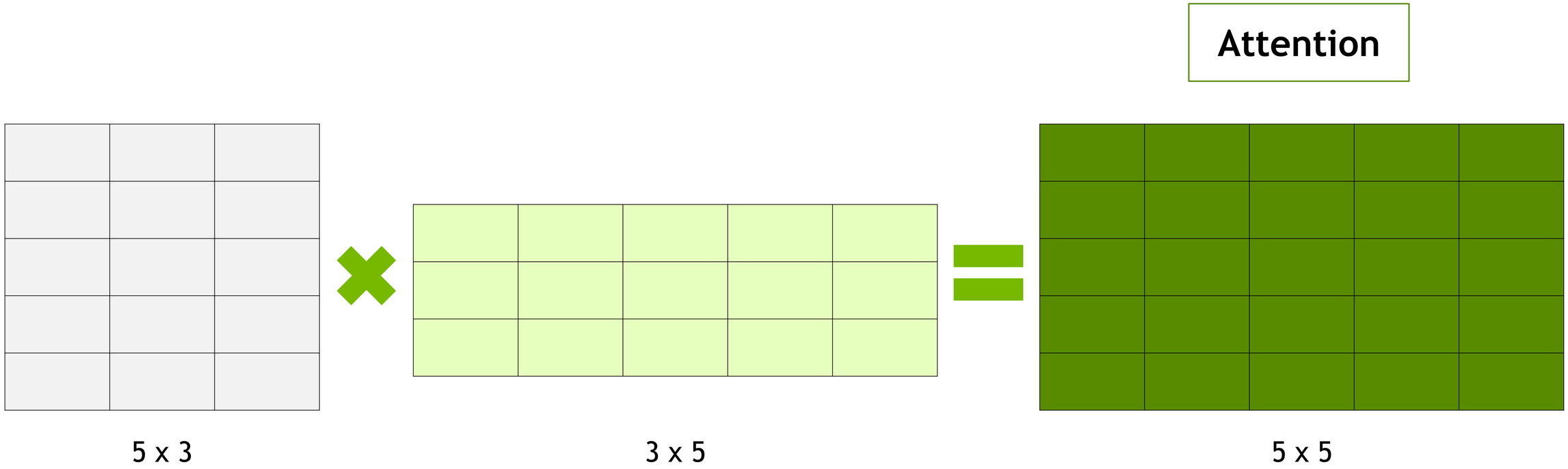


5 x 3

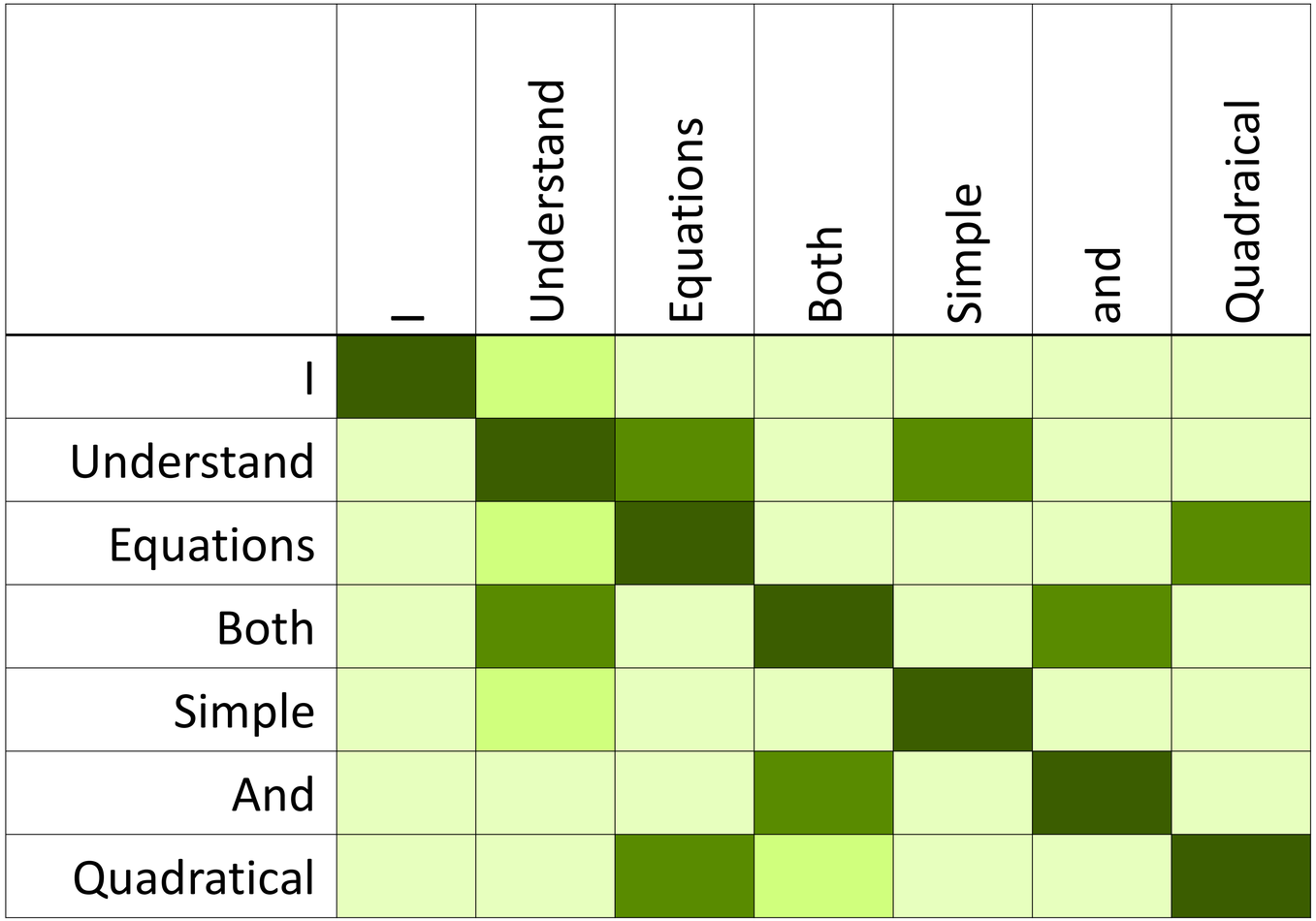


3 x 5

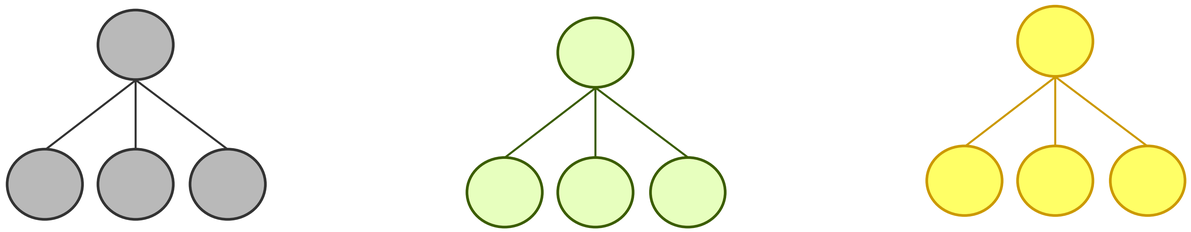
# Attention



# Attention


I
Understand
Equations
Both
Simple
and
Quadraical
I
Understand
Equations
Both
Simple
And
Quadratical

# Attention



| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| I | | | | | | | | | |
| am | | | | | | | | | |
| the | | | | | | | | | |
| very | | | | | | | | | |
| model | | | | | | | | | |

5 x 3

Q

Query

5 x 3

K

Key

5 x 3

V

Value

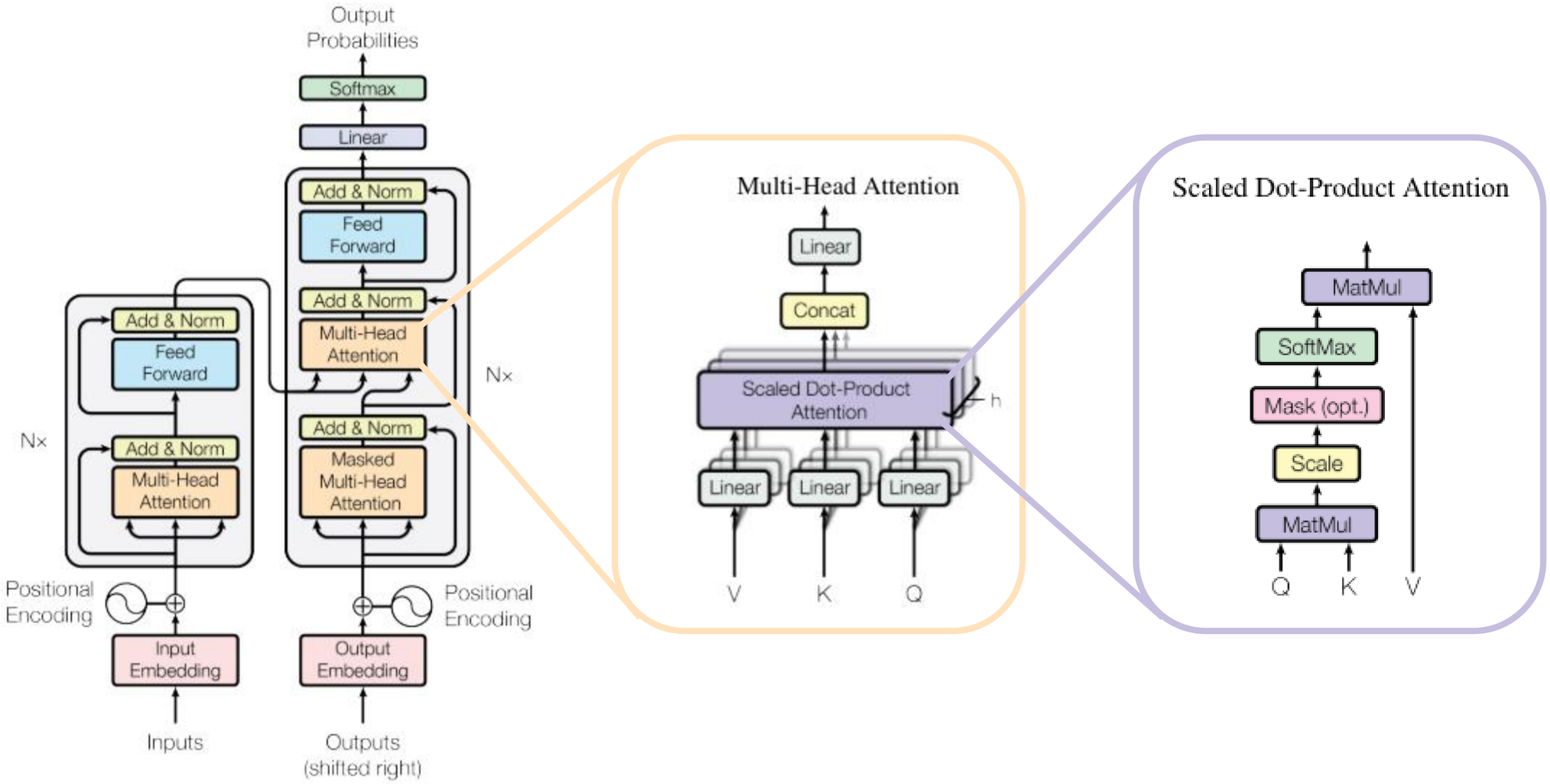
# Attention

$$Z = softmax\left(\frac{Q \times K^T}{\sqrt{d_k}}\right)V$$

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| I | | | | | | | | | | | | |
| am | | | | | | | | | | | | |
| the | | | | | | | | | | | | |
| very | | | | | | | | | | | | |
| model | | | | | | | | | | | | |

| 5 x 3 | 5 x 3 | 5 x 3 | 5 x 3 |
|---|---|---|---|
| Q | K | V | Z |
| Query | Key | Value | Attention Score |

# Transformers



# BERT

## BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

**Jacob Devlin** **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

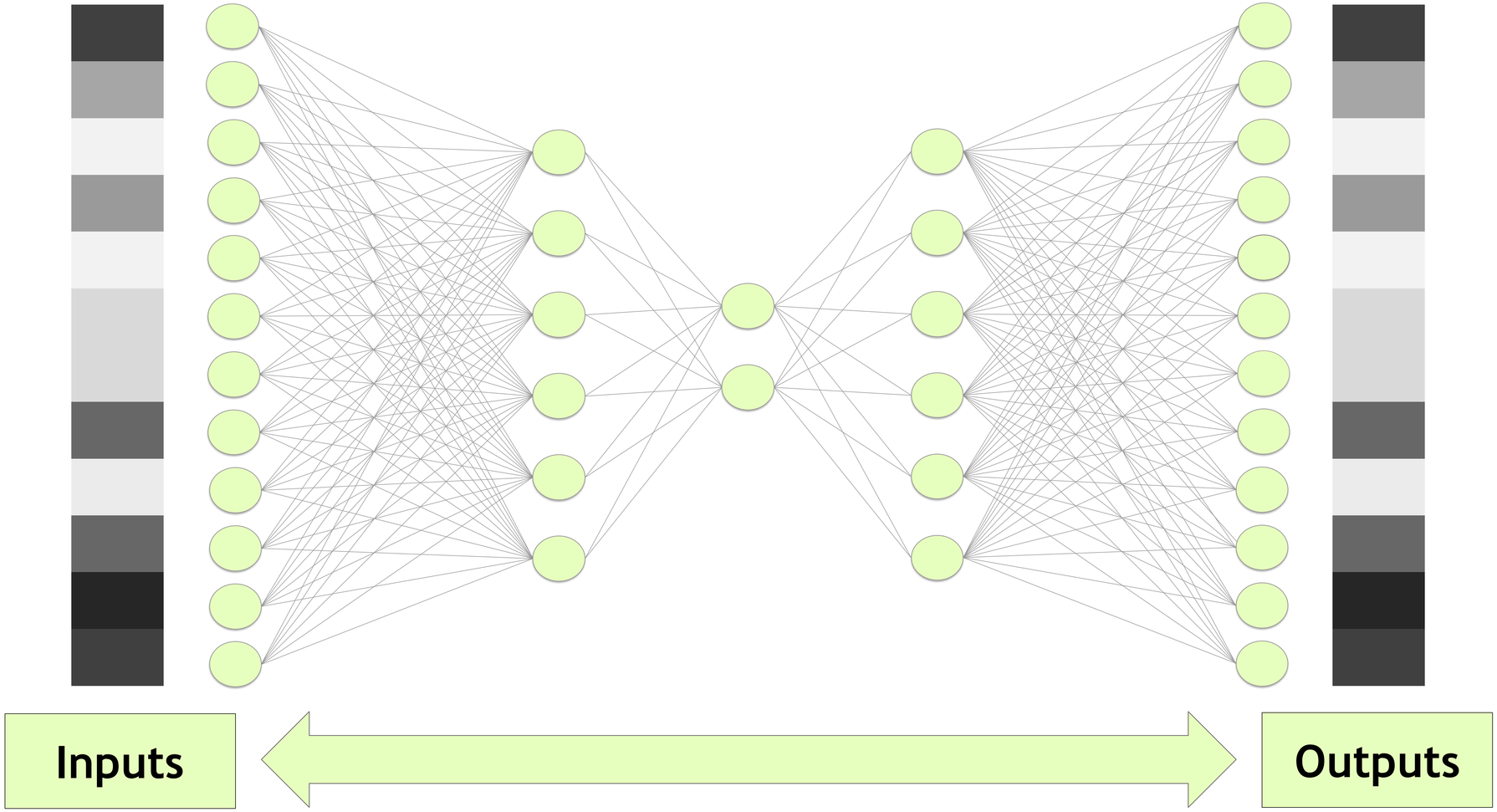
### Abstract

We introduce a new language representation model called **BERT**, which stands for **B**idirectional **E**ncoder **R**epresentations from

There are two existing strategies for applying pre-trained language representations to downstream tasks: *feature-based* and *fine-tuning*. The feature-based approach, such as ELMo (Peters

# Other Architectures

# Autoencoders



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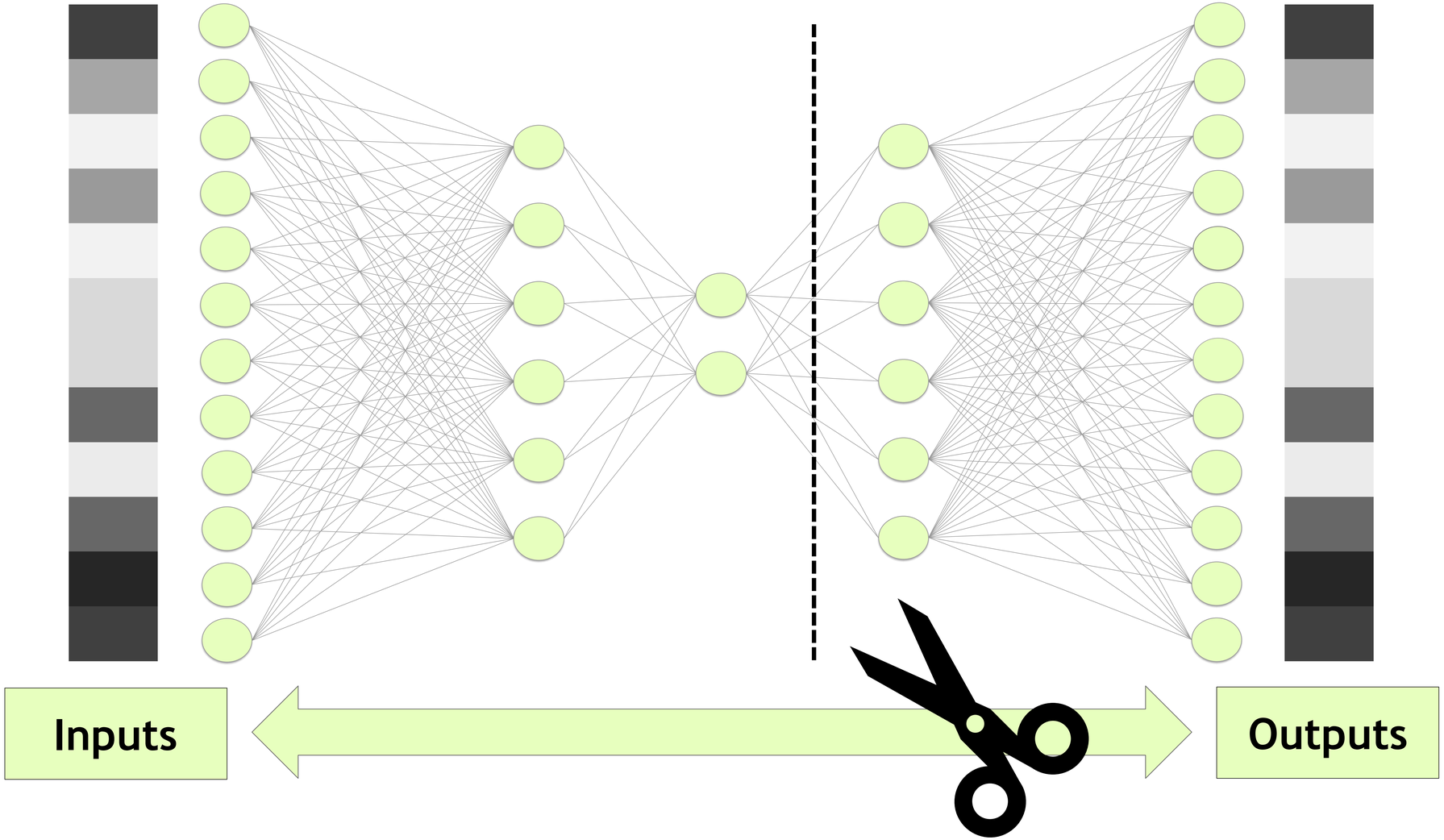

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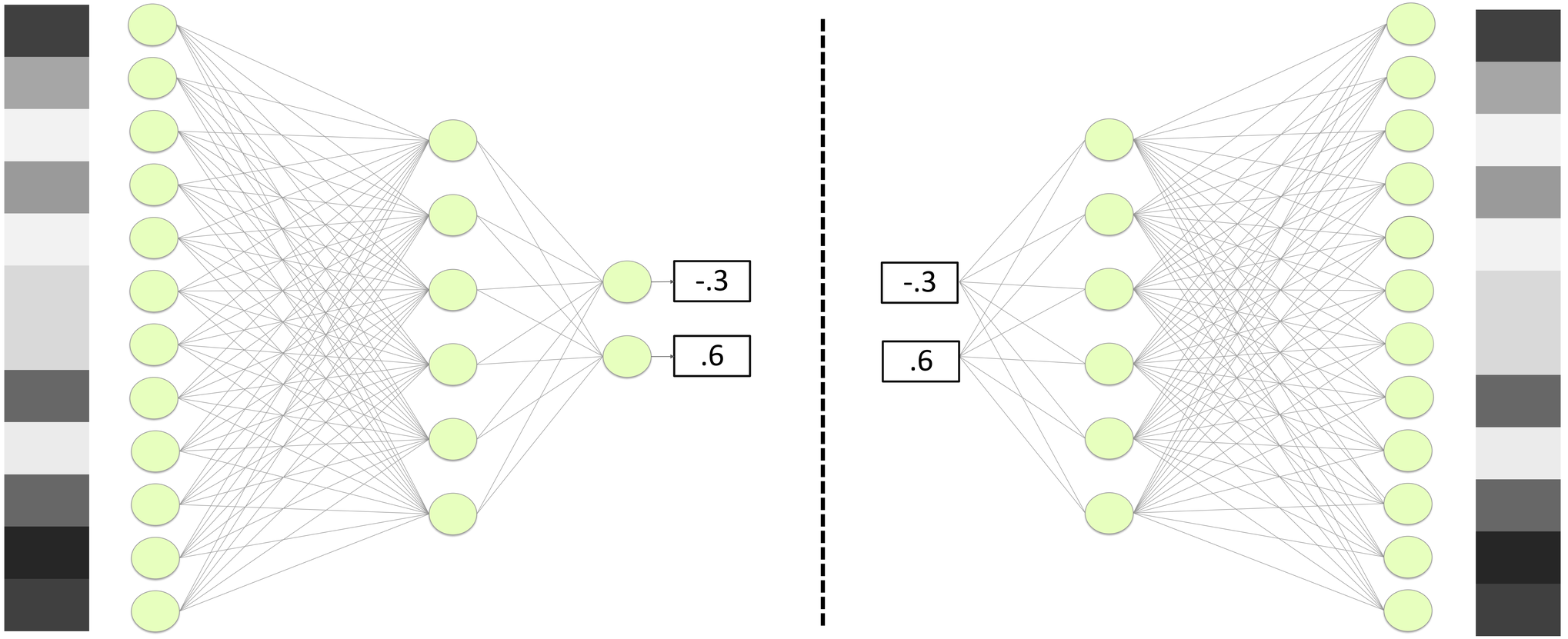
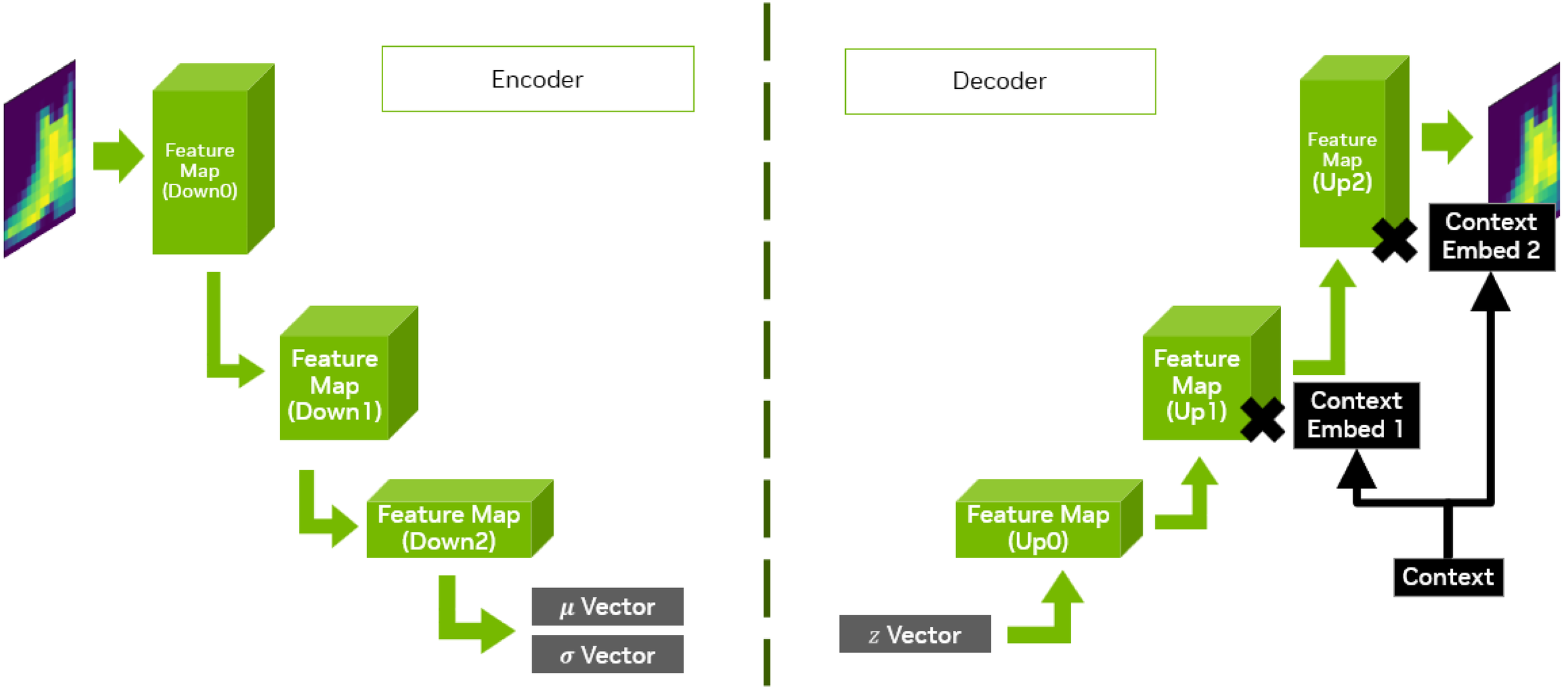


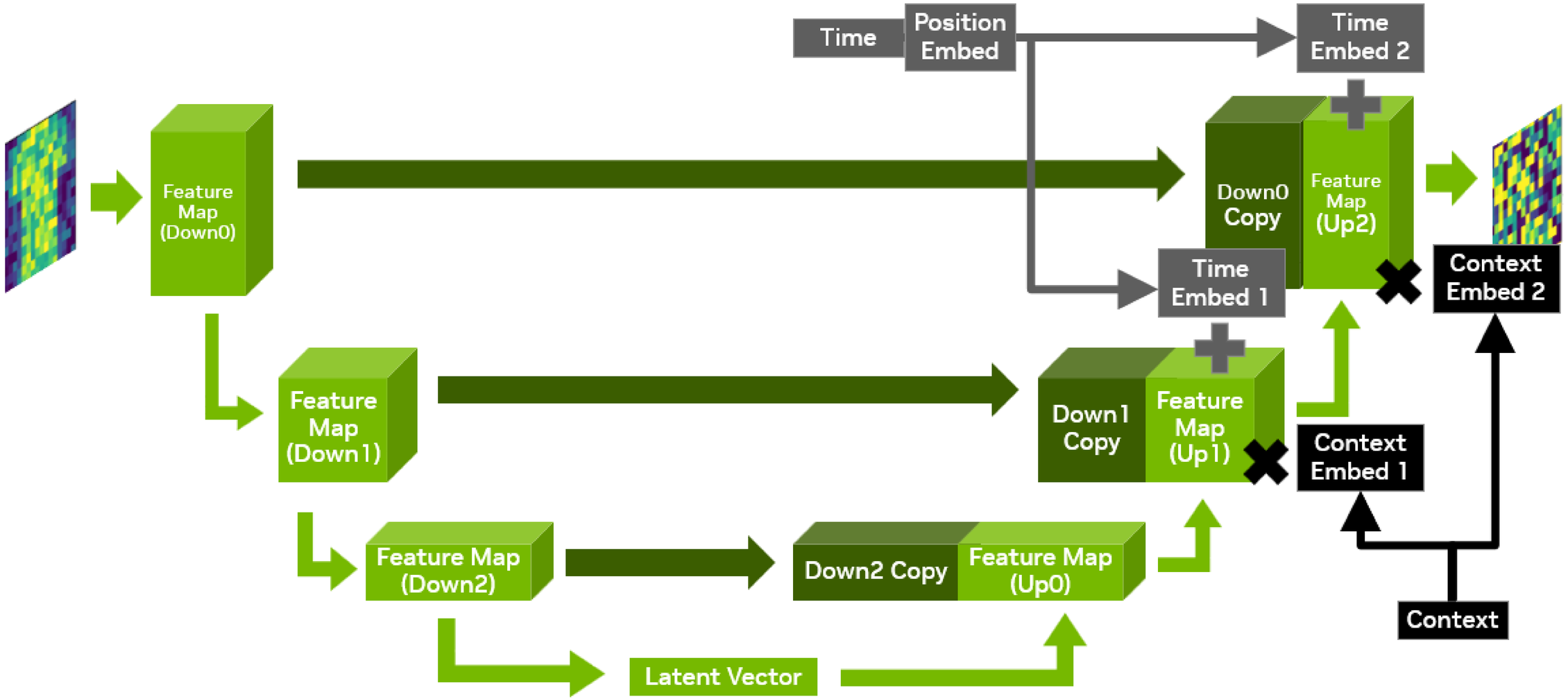

Encoder

Decoder

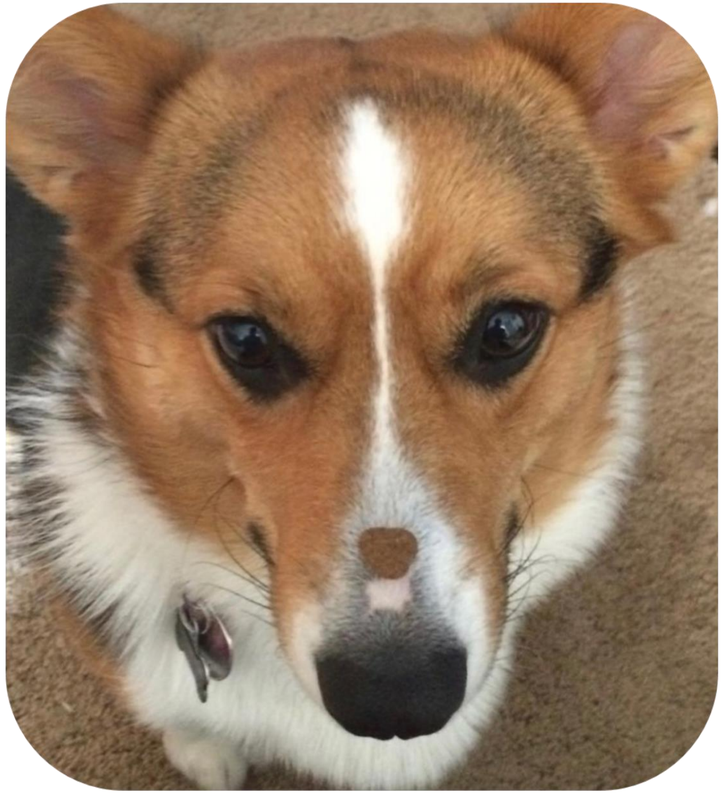
# Variational Autoencoder

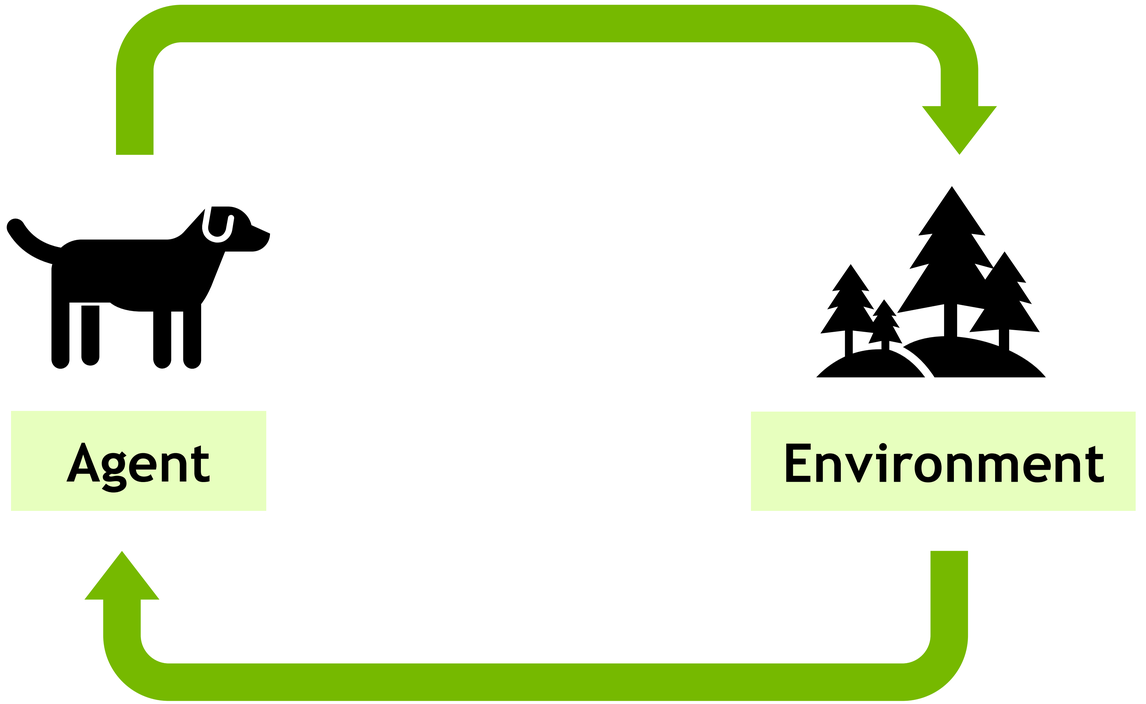


# Diffusion Models



# Reinforcement Learning





# Next Steps

# ENABLING PORTABILITY WITH NGC CONTAINERS

## Extensive

- Diverse range of workloads and industry specific use cases

## Optimized

- DL containers updated monthly
- Packed with latest features and superior performance

## Secure & Reliable

- Scanned for vulnerabilities and crypto
- Tested on workstations, servers, & cloud instances

## Scalable

- Supports multi-GPU & multi-node systems

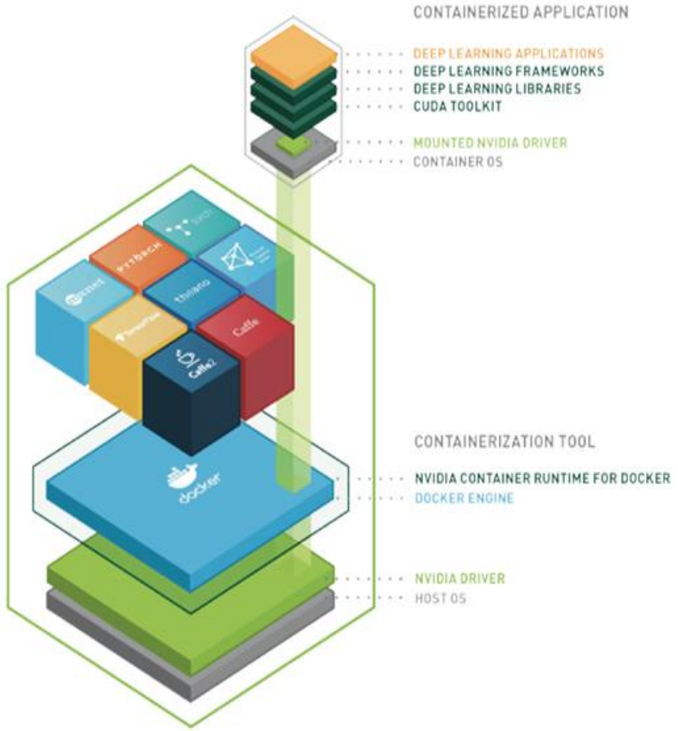
## Designed for Enterprise & HPC

- Supports Docker, Singularity & other runtimes

## Run Anywhere

- Bare metal, VMs, Kubernetes
- x86, ARM, POWER
- Multi-cloud, on-prem, hybrid, edge

## NGC Deep Learning Containers




CONVERSATIONAL AI — Riva

HEALTHCARE — CLARA

SMART CITIES — DEEPSTREAM & SMART PARKING

TELECOM — AERIAL

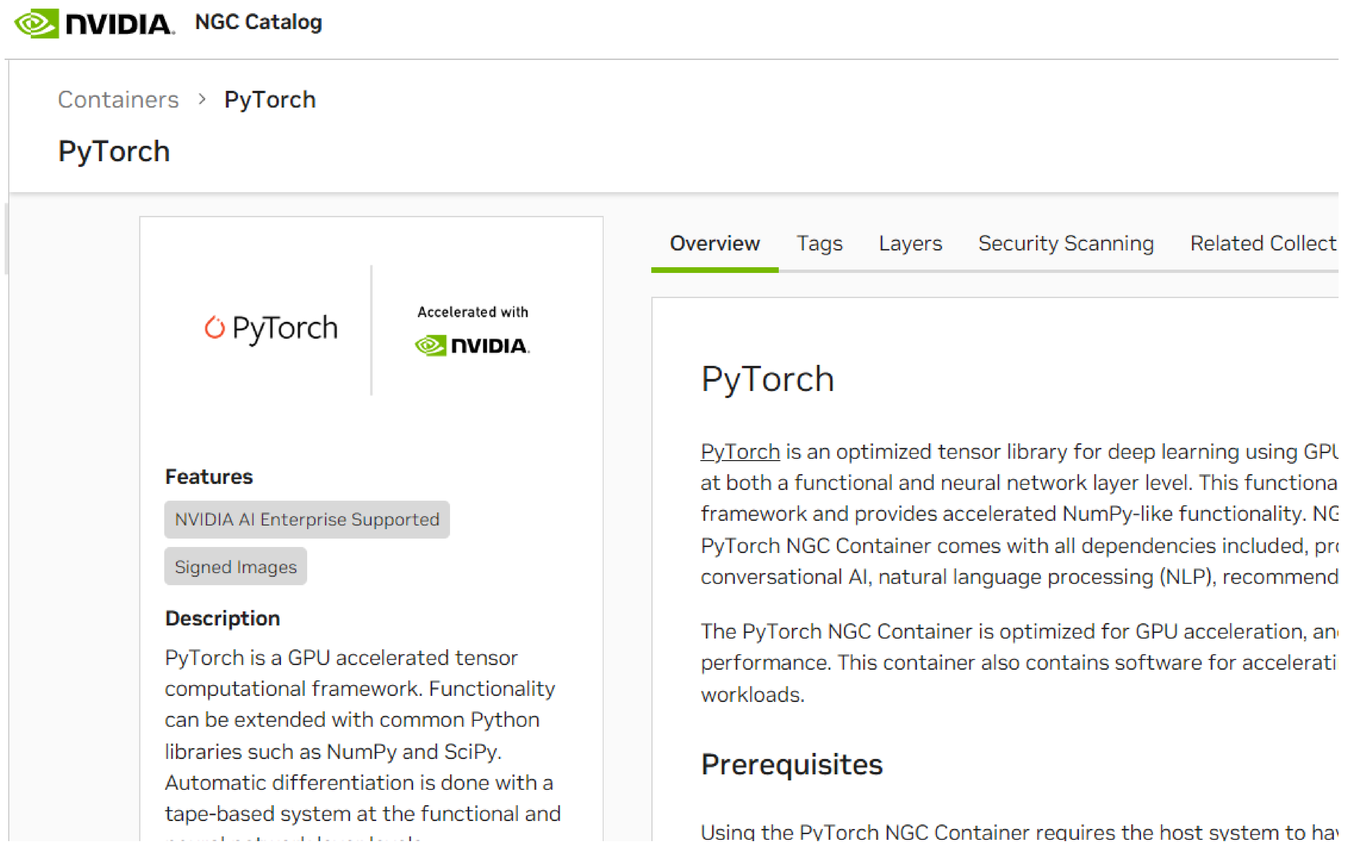
AUTONOMOUS DRIVING — DRIVE

ROBOTICS — ISAAC

HPC — HPC SDK

Learn more about NGC Containers

# Next Steps for This Class




**Step 1** Sign up for NGC

https://docs.nvidia.com/dgx/ngc-registry-for-dgx-user-guide/index.html

**Step 2** Visit NGC Catalog

https://catalog.ngc.nvidia.com/orgs/nvidia/containers/pytorch

**Step 3** Pull and Run Container

Visit localhost:8888 to check out a JupyterLab environment

# Closing Thoughts

# Copying Rocket Science

# Let’s get Started!