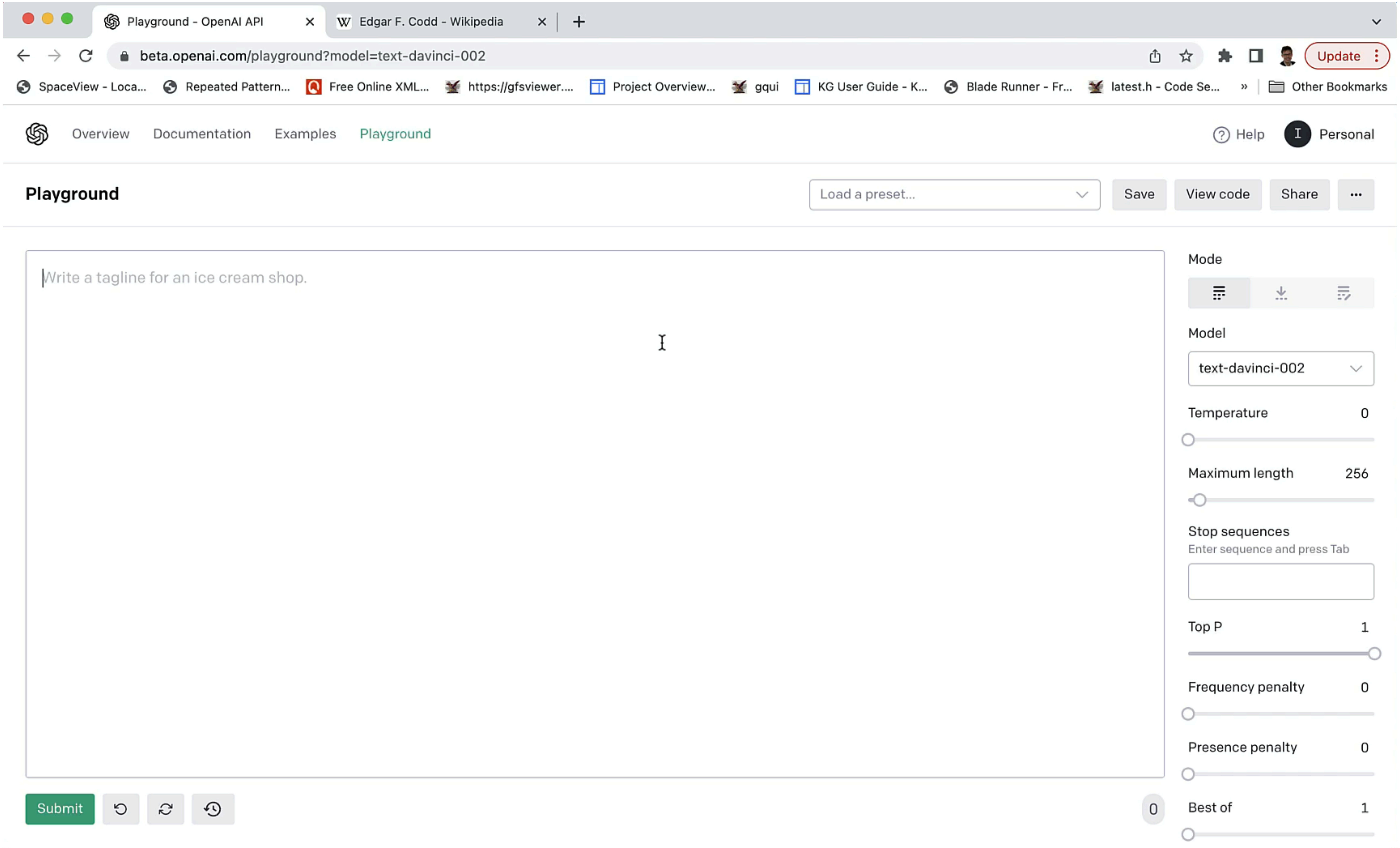
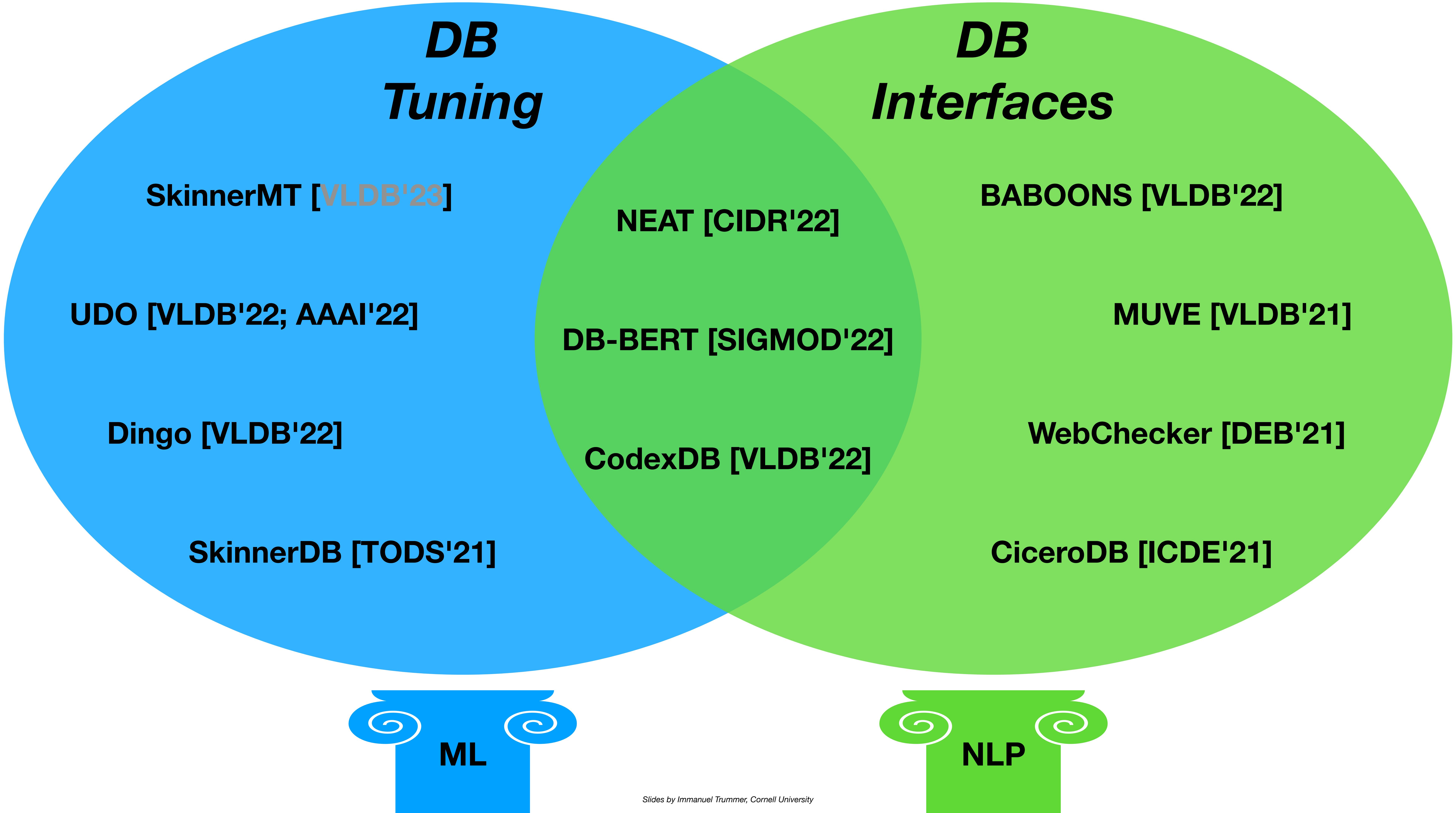
From BERT to GPT-3 Codex: Harnessing the Potential of Very Large Language Models for Data Management

Immanuel Trummer

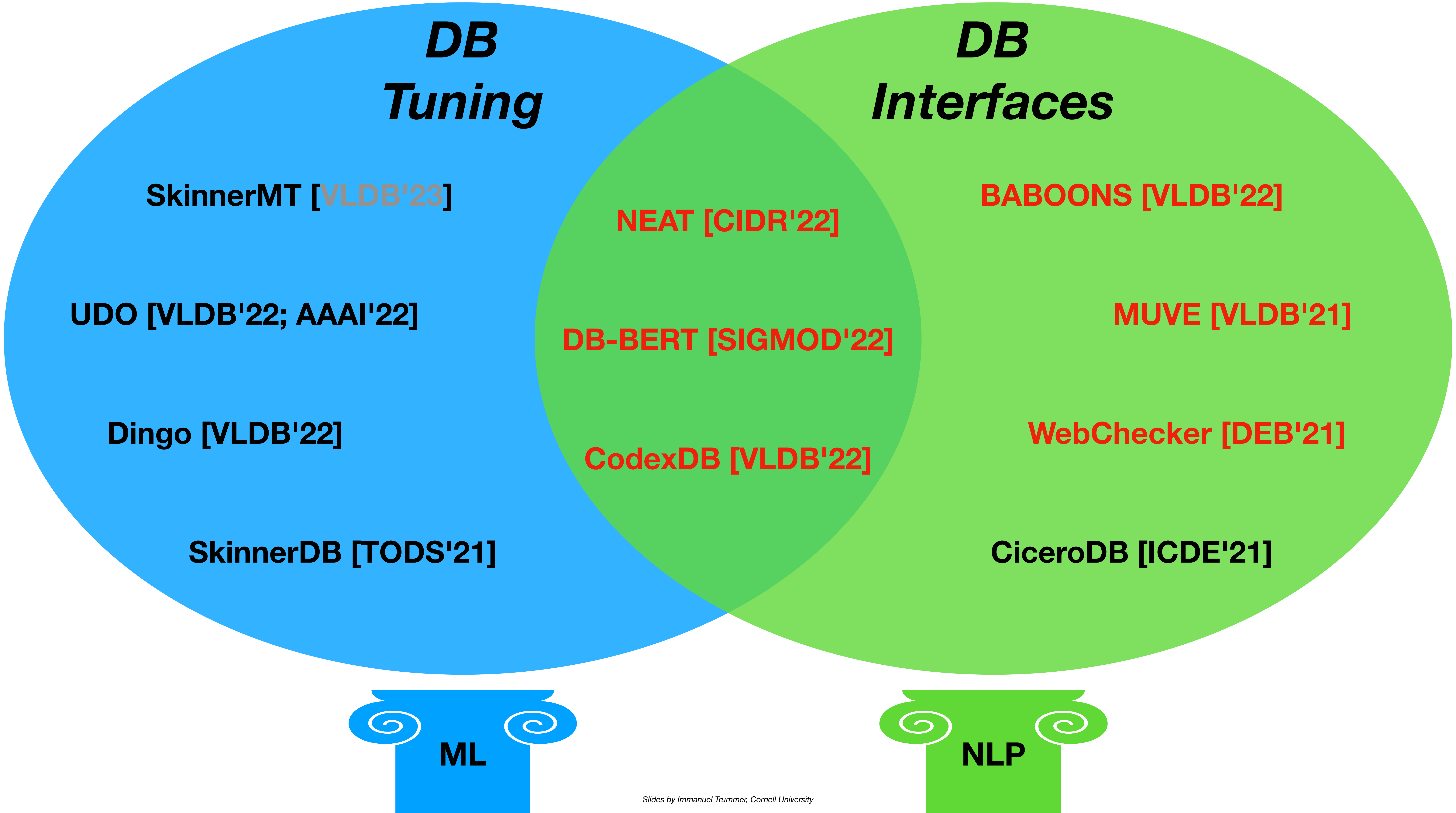

Playground - OpenAI API
Edgar F. Codd - Wikipedia
beta.openai.com/playground?model=text-davinci-002
Update
SpaceView - Loca...
Repeated Pattern...
Free Online XML...
https://gfsviewer....
Project Overview...
gqui
KG User Guide - K...
Blade Runner - Fr...
latest.h - Code Se...
Other Bookmarks
Overview
Documentation
Examples
Playground
Help
Personal
Playground
Load a preset...
Save
View code
Share
Write a tagline for an ice cream shop.
Mode
Model
text-davinci-002
Temperature 0
Maximum length 256
Stop sequences
Enter sequence and press Tab
Top P 1
Frequency penalty 0
Presence penalty 0
Best of 1
Submit
0

My Background

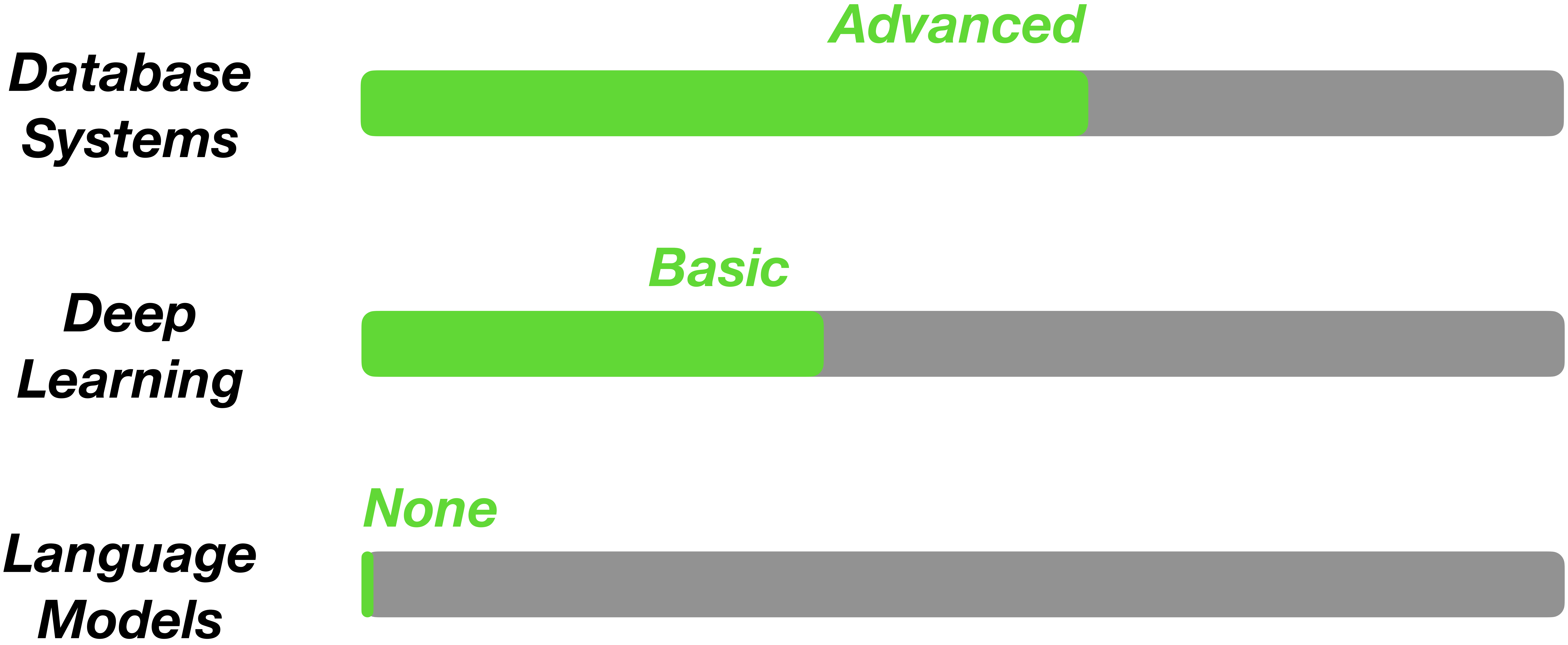


My Background

Uses Language Models



Target Audience



Tutorial Goal

Database Systems — Advanced

Deep Learning — Basic

Language Models — Basic

Tutorial Outline

1. **Transformer** Architecture
2. **Transfer** Learning
3. **Libraries** and Interfaces
4. **Applications** in Data Management

https://itrummer.github.io/lm4db/

?

The Transformer Model

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly

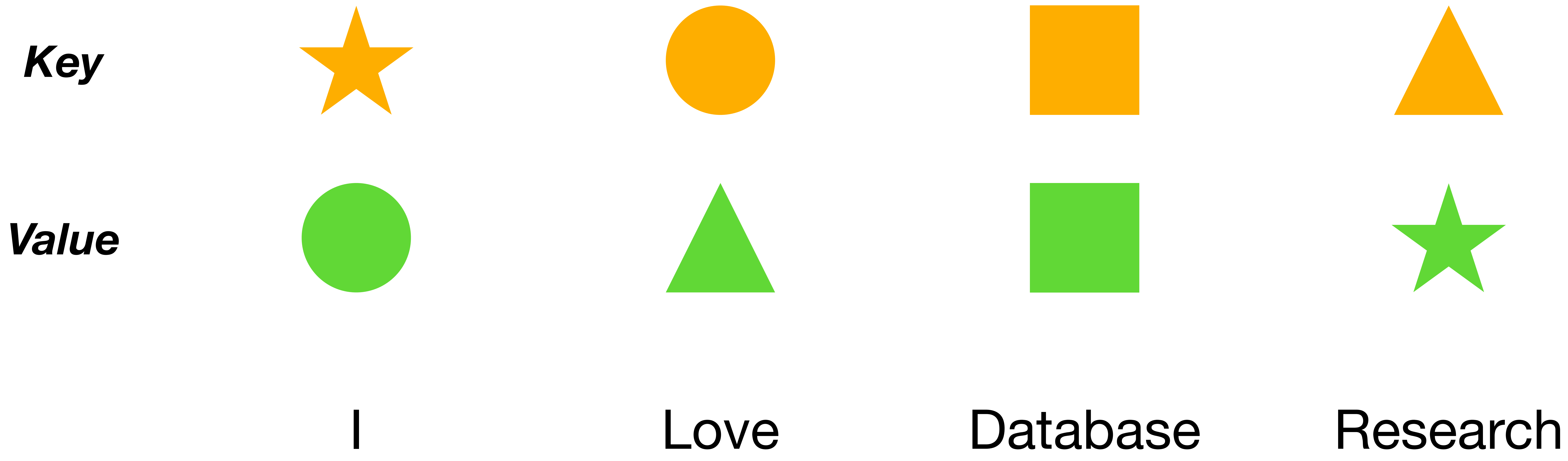
Attention Mechanism vs. Key-Value Stores

- Shared **vocabulary**:
  - Keys, values, queries
- Similar **semantics**:
  - Find keys matching query
  - Retrieve associated values

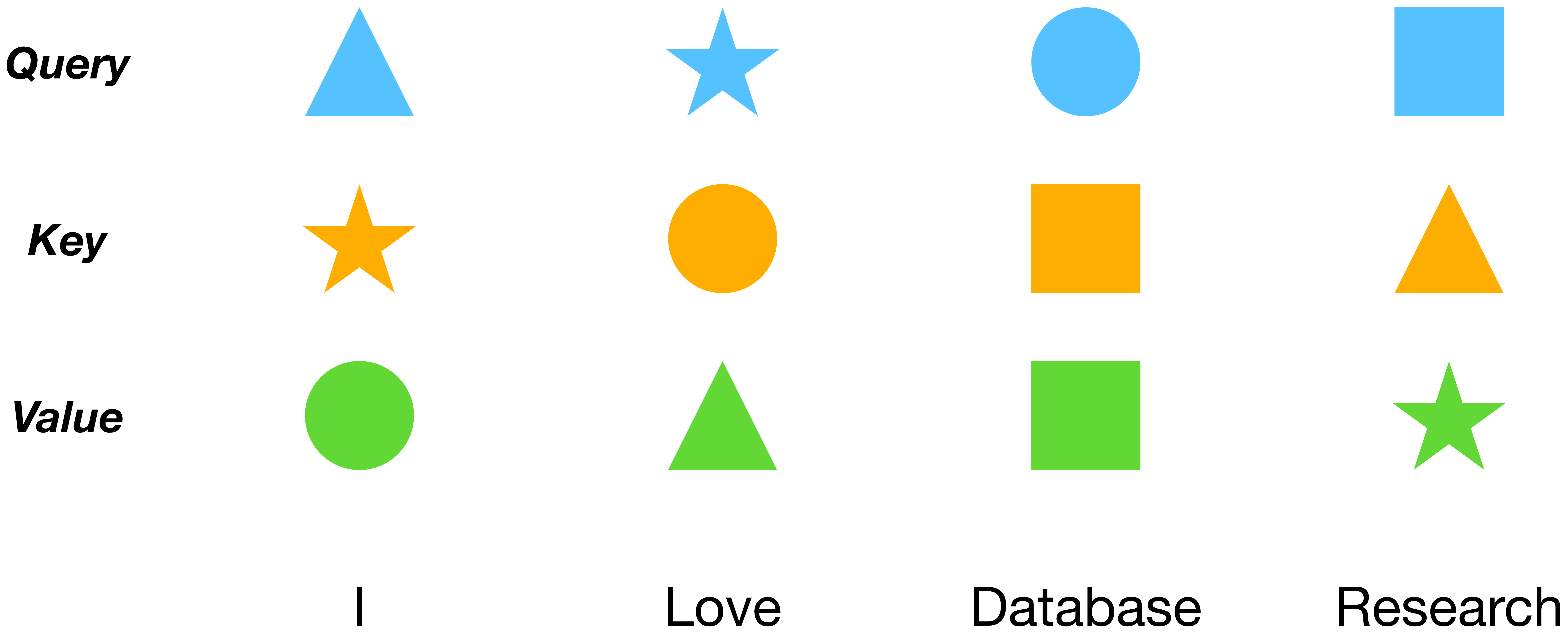
Attention: Simplifying Intuition

I Love Database Research

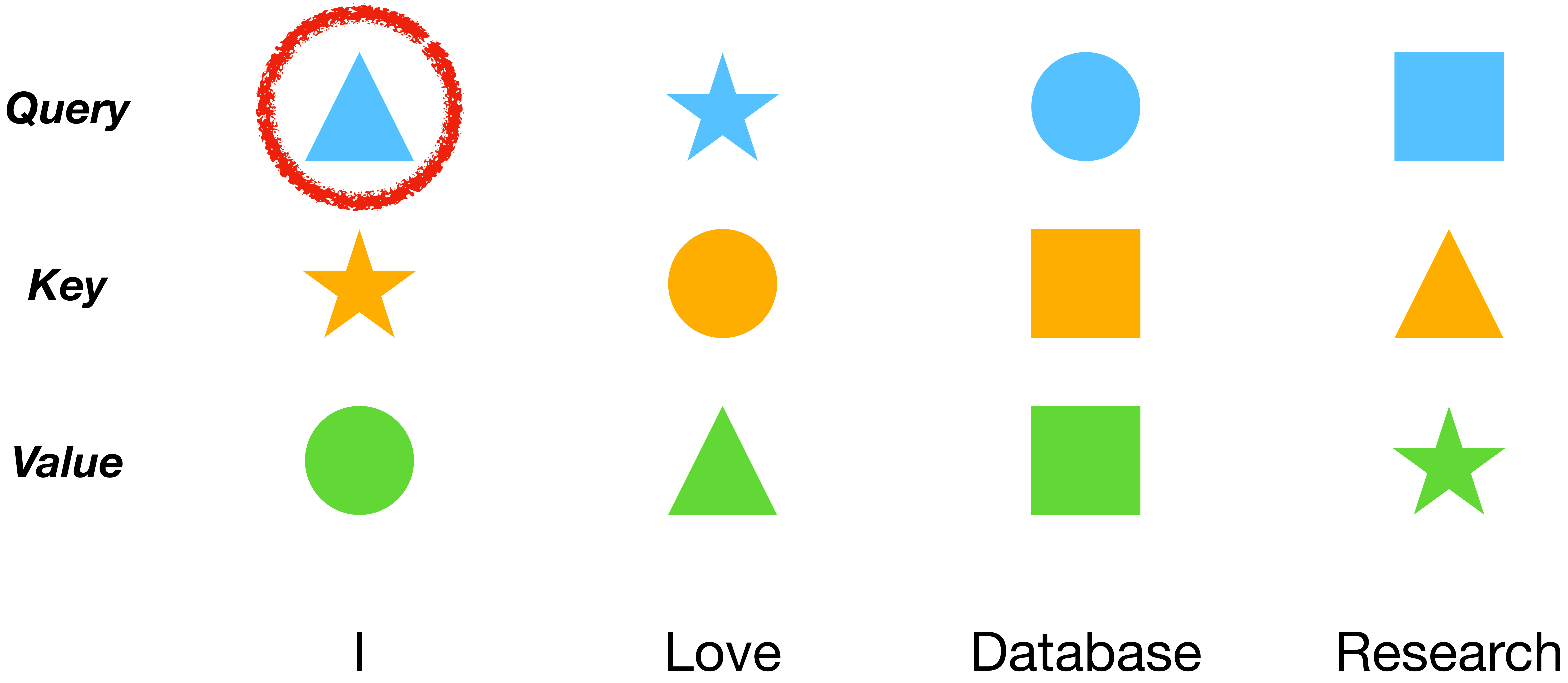
Attention: Simplifying Intuition



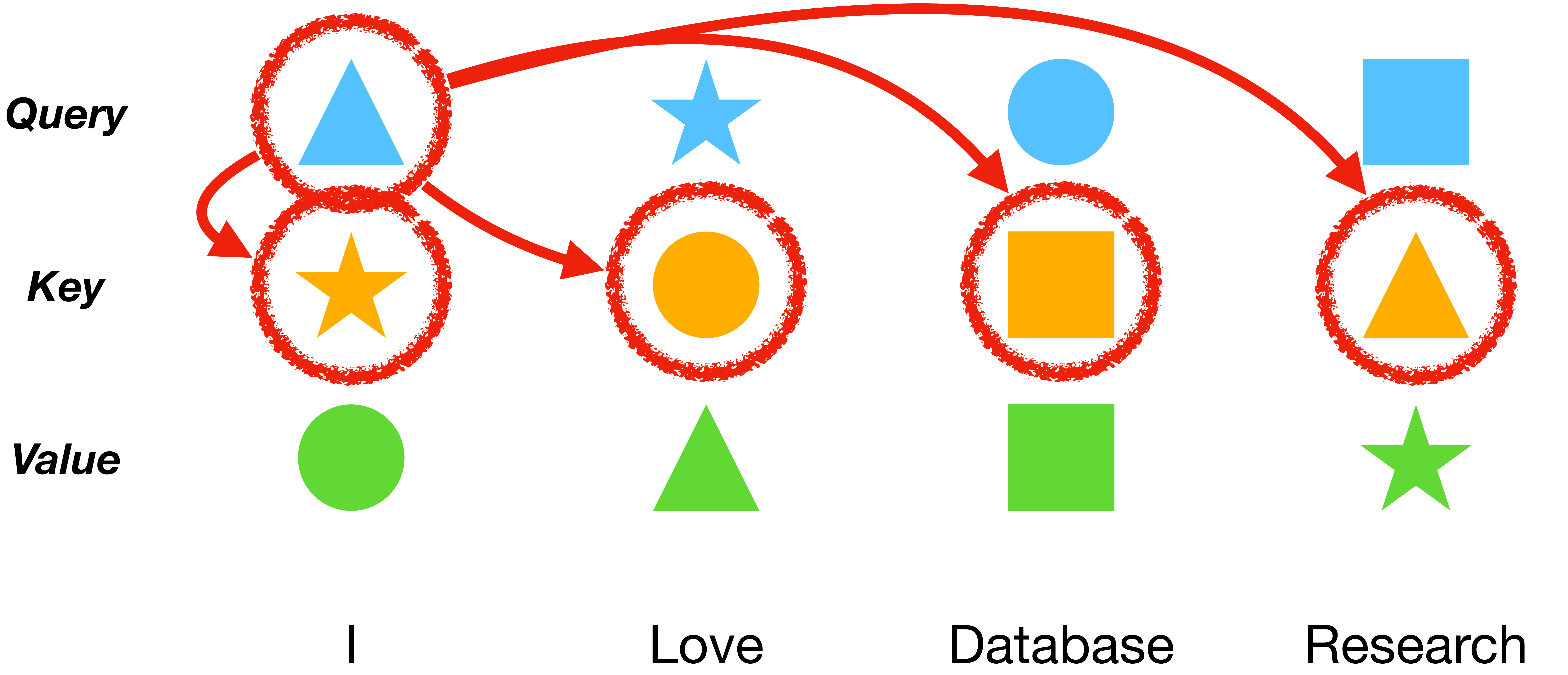
Attention: Simplifying Intuition



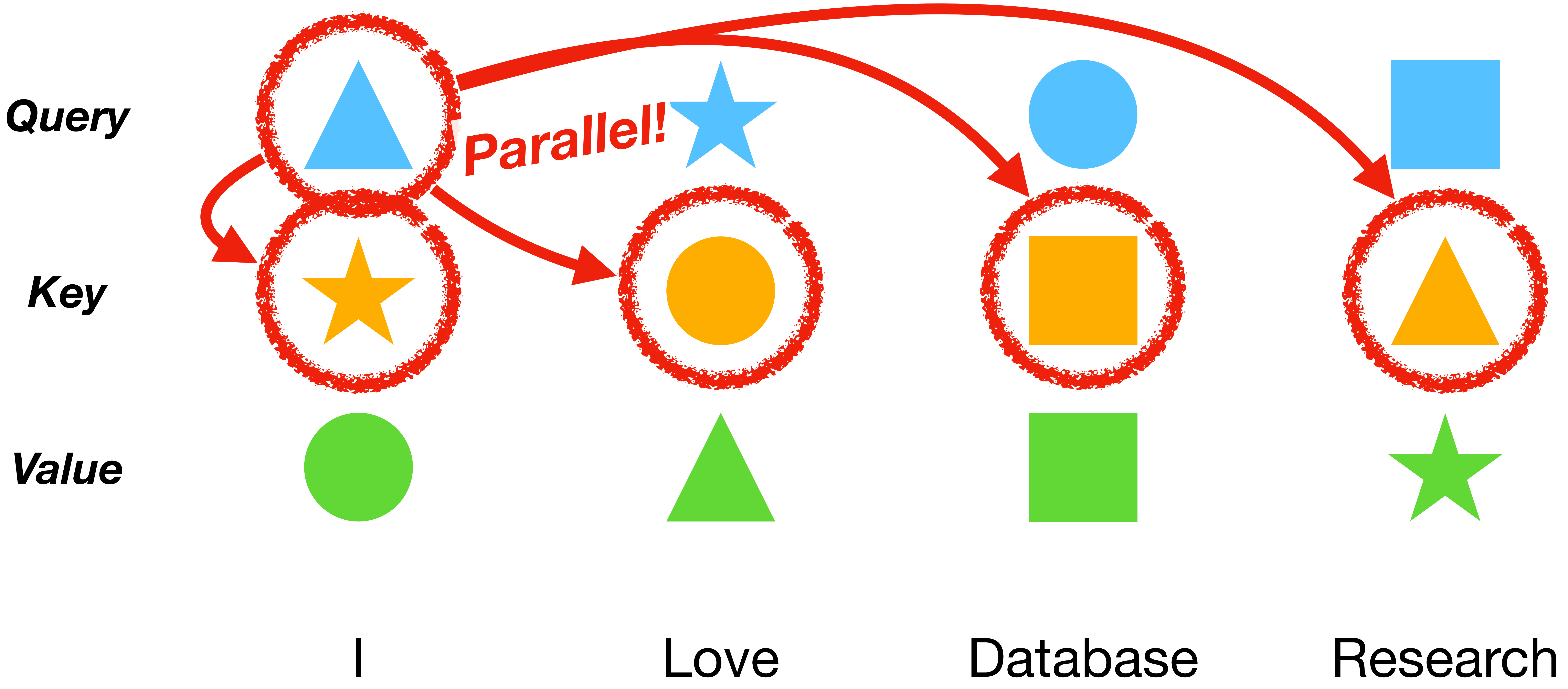
Attention: Simplifying Intuition



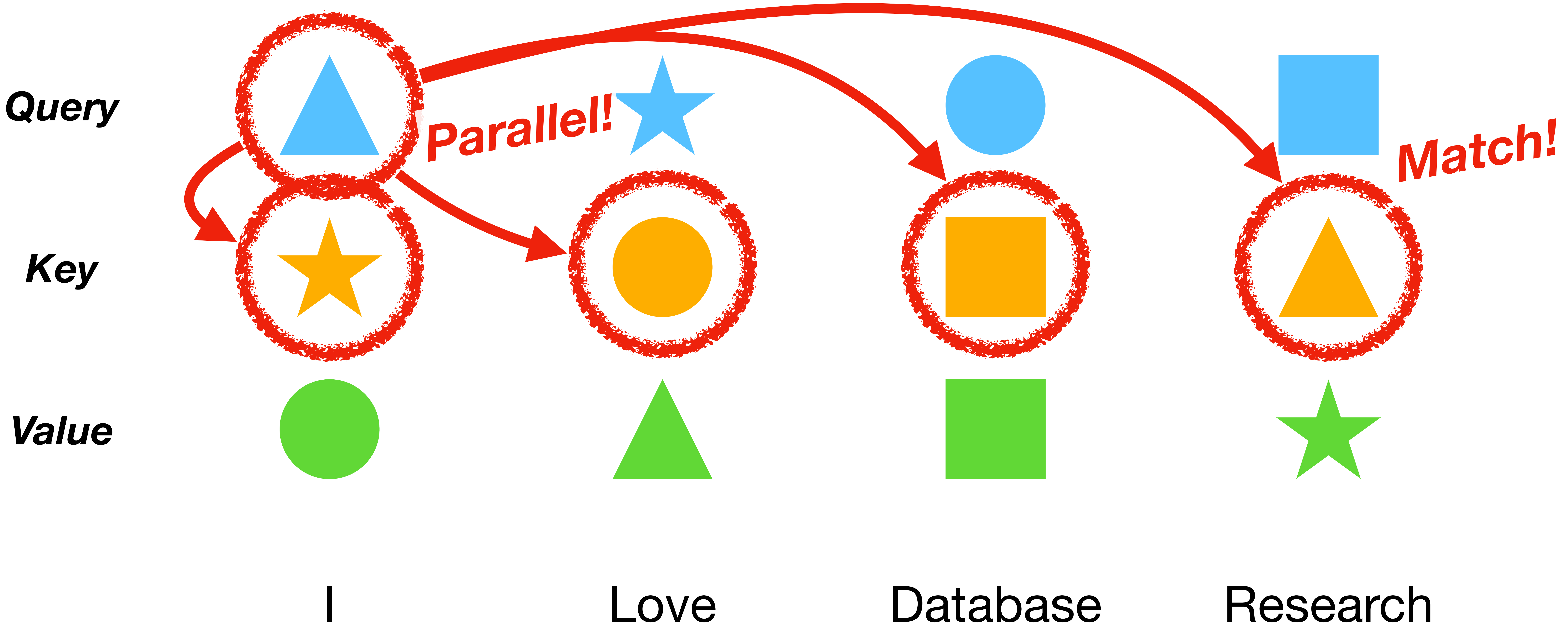
Attention: Simplifying Intuition



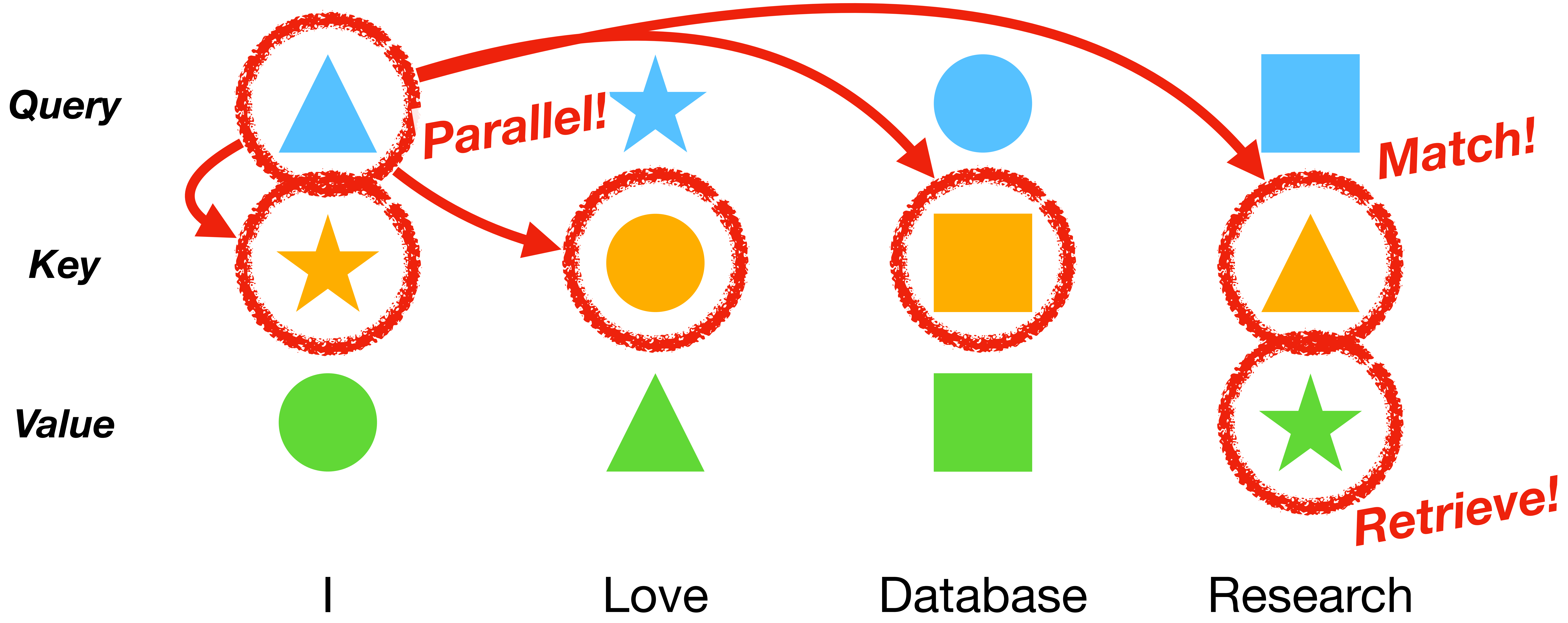
Attention: Simplifying Intuition



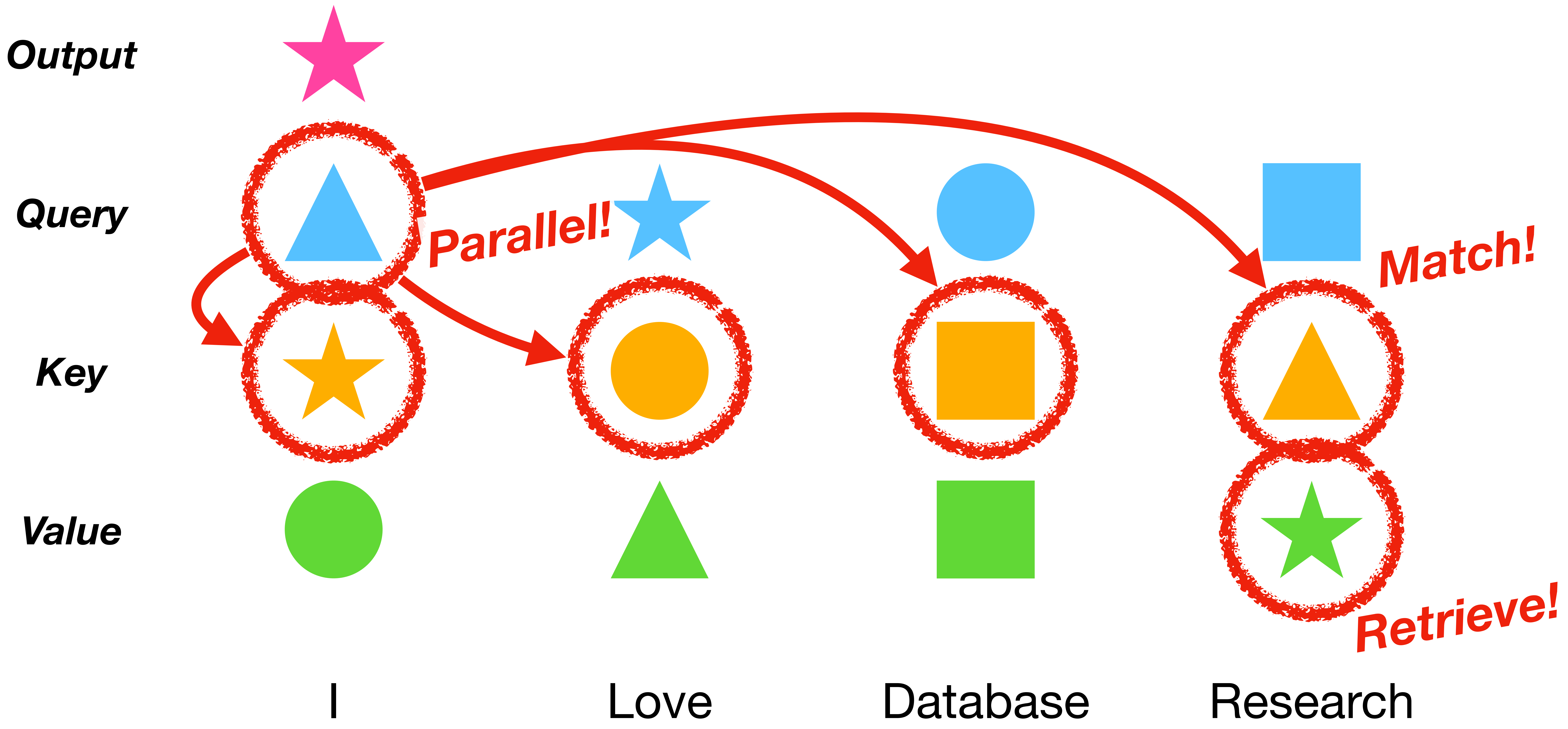
Attention: Simplifying Intuition



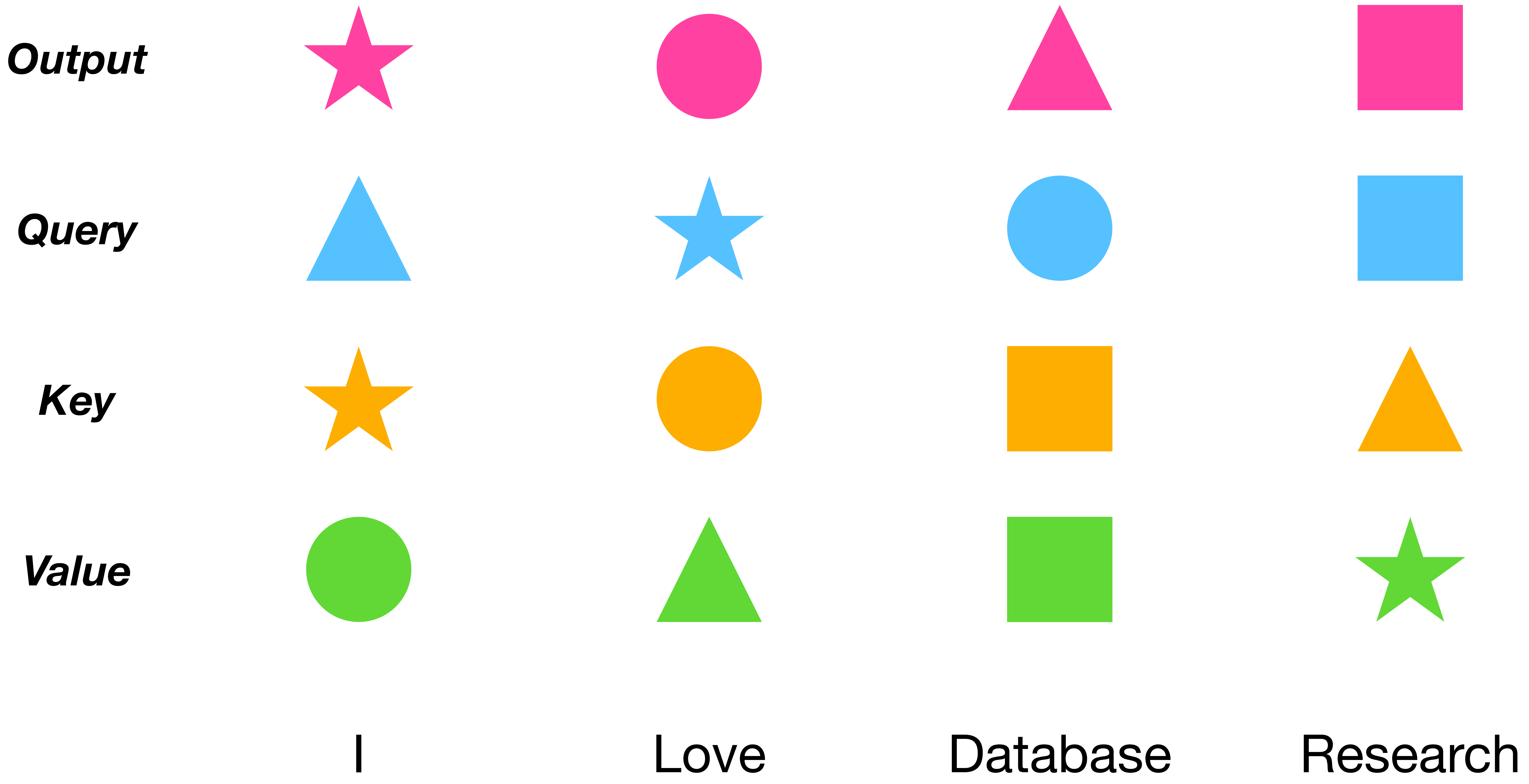
Attention: Simplifying Intuition



Attention: Simplifying Intuition



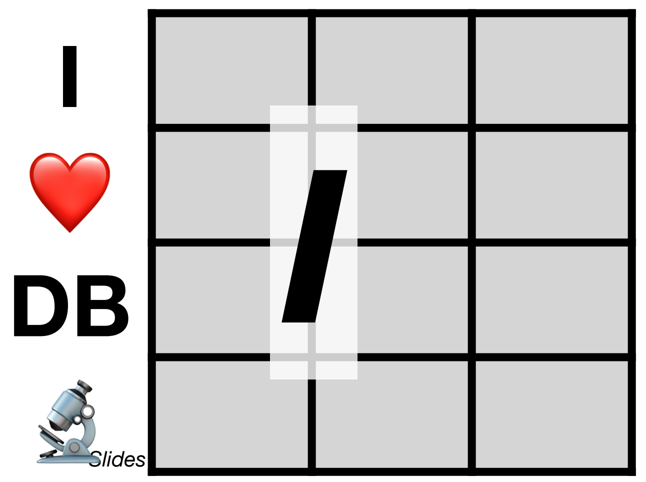
Attention: Simplifying Intuition



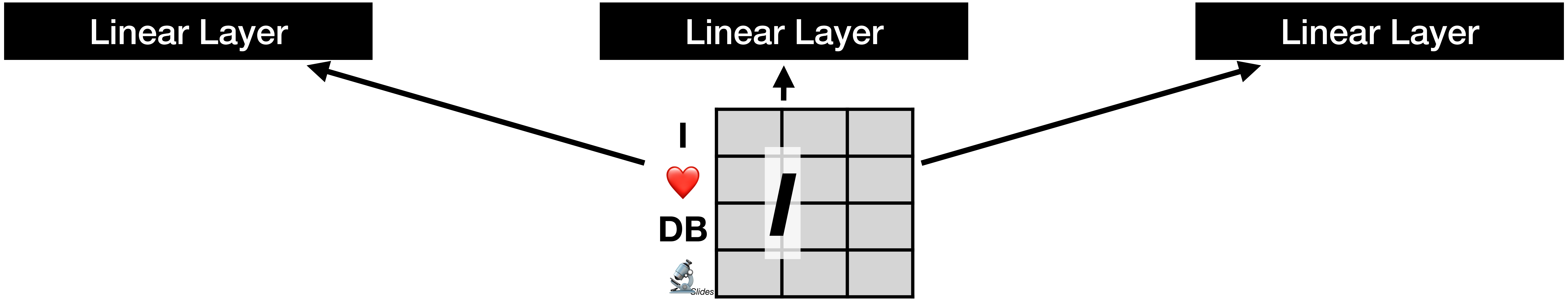
Attention vs. Simplifying Intuition

- Real-valued **vectors** instead of discrete symbols
- Continuous **similarity** between queries and keys
- Output value is **sum** of values, weighted by similarity
- Several **normalization** steps

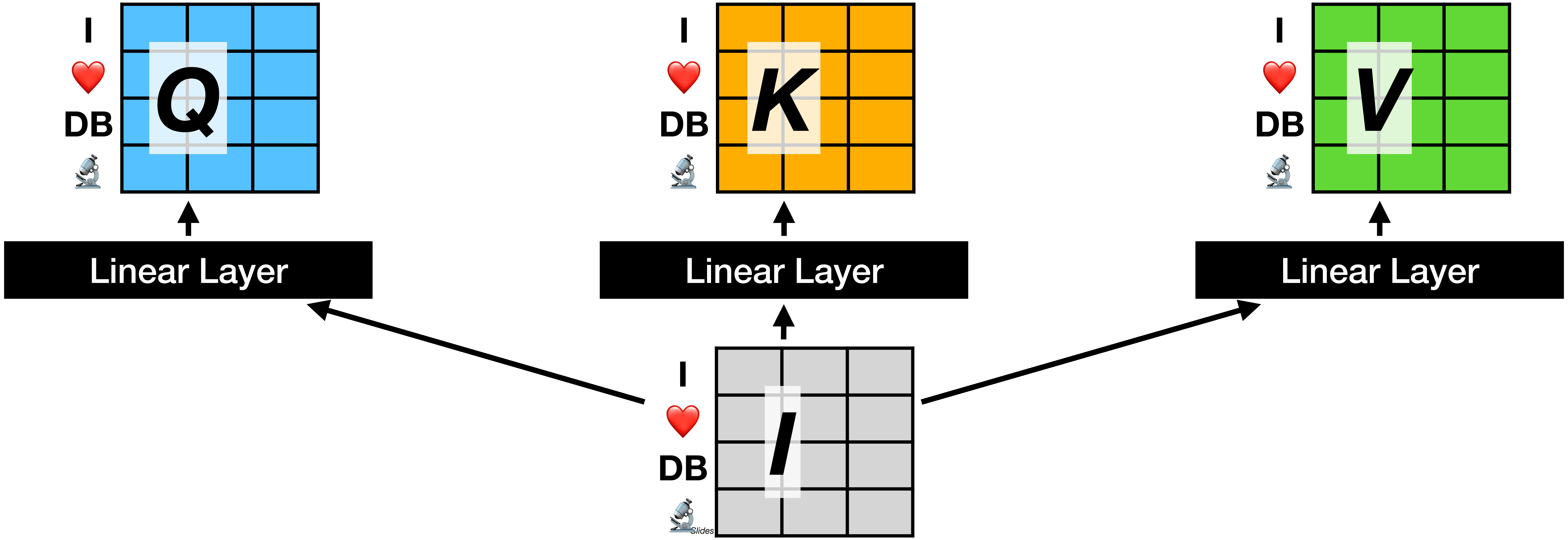
Attention



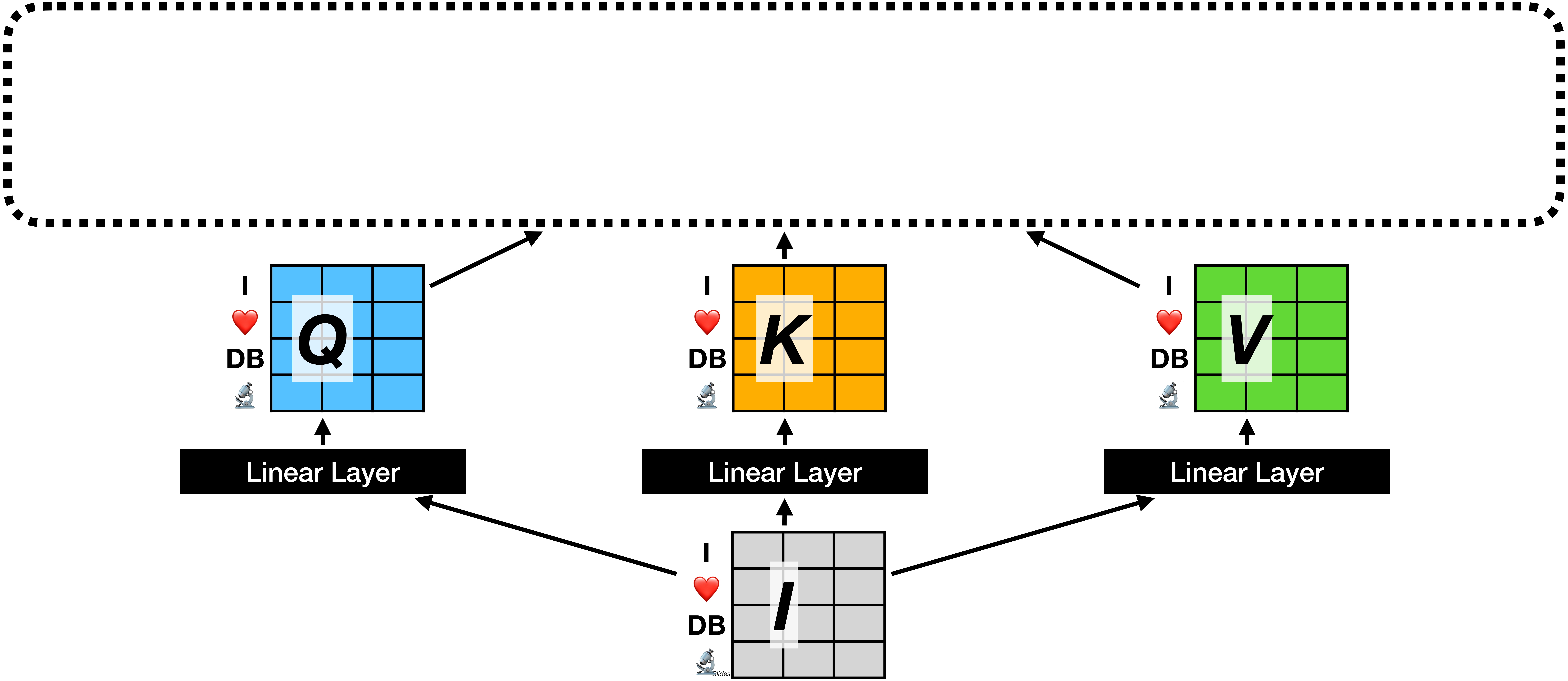
Attention



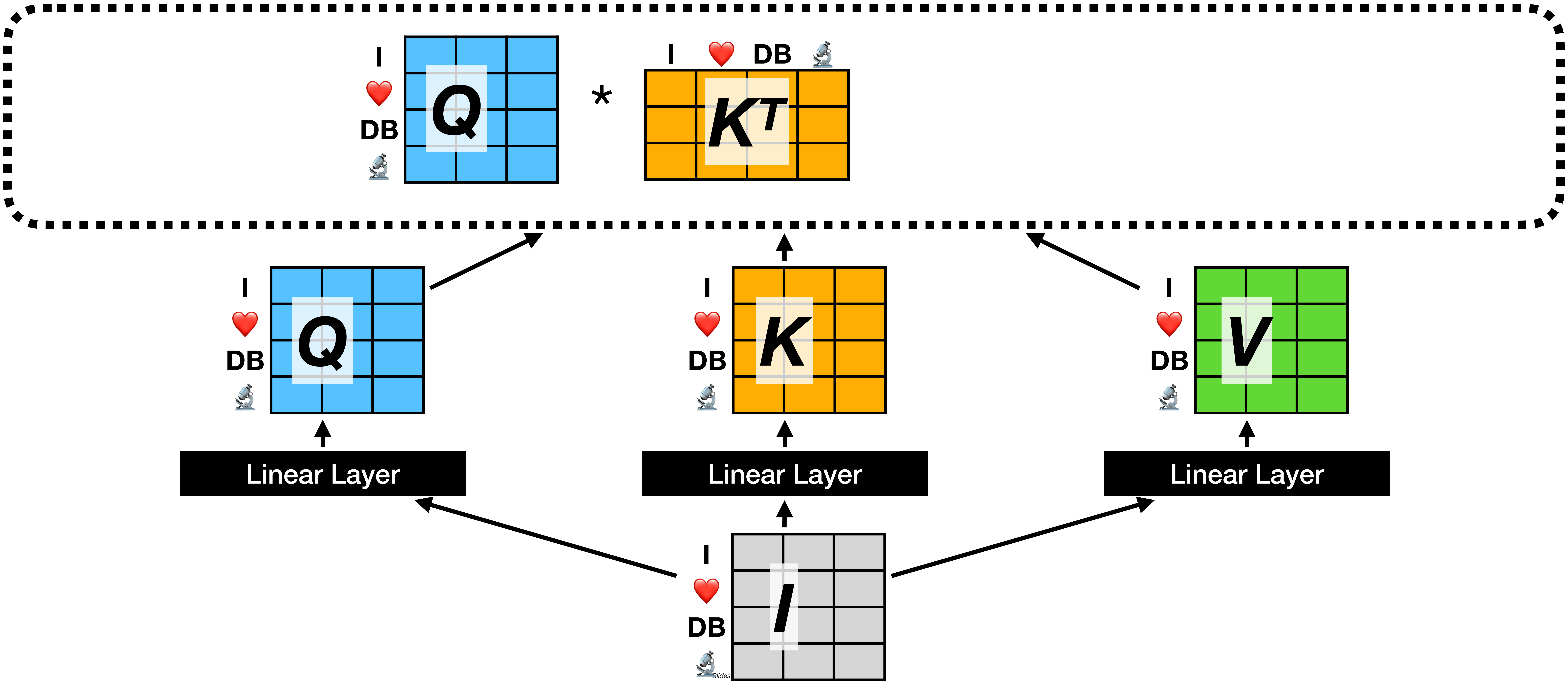
Attention



Attention

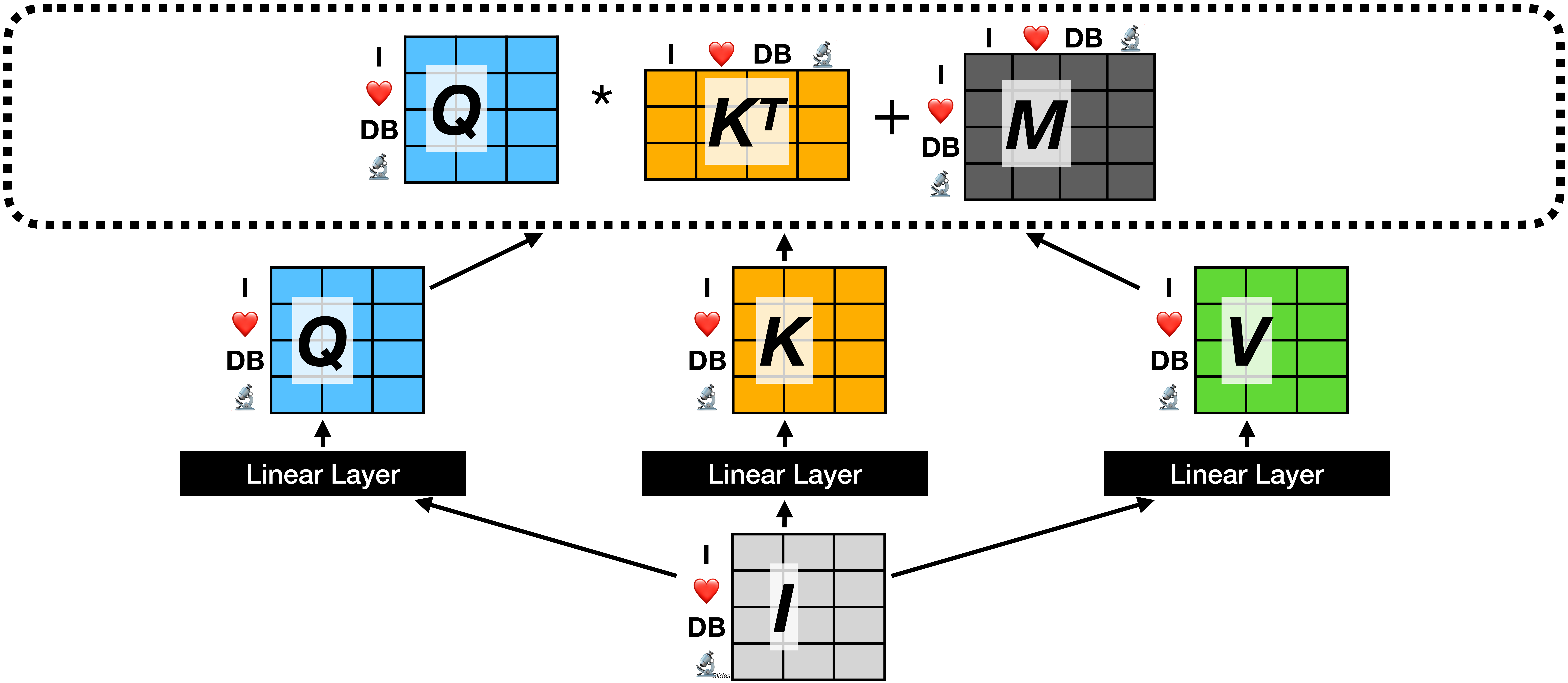


Attention

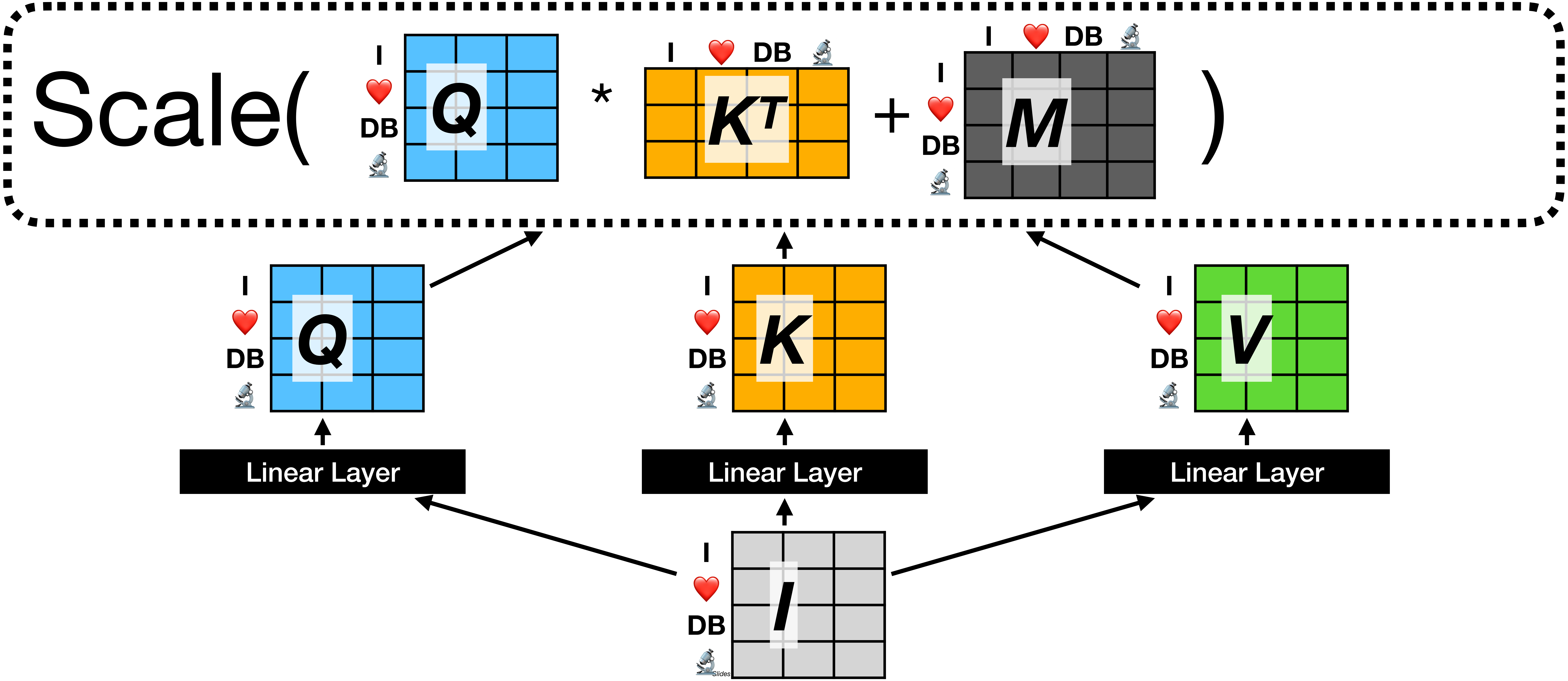


I
DB
Q
*
I
DB
K^T
I
DB
Q
I
DB
K
I
DB
V
Linear Layer
Linear Layer
Linear Layer
I
DB
I

Attention

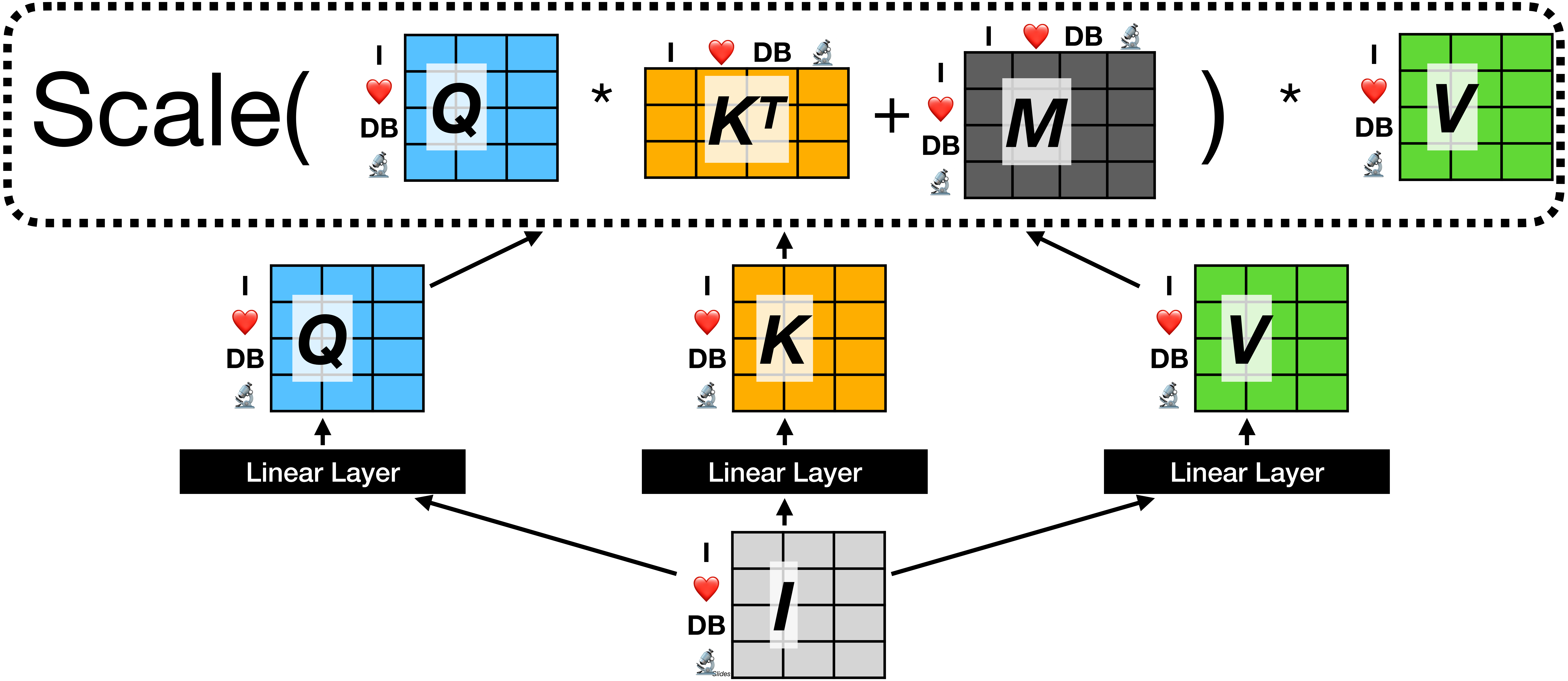


Attention



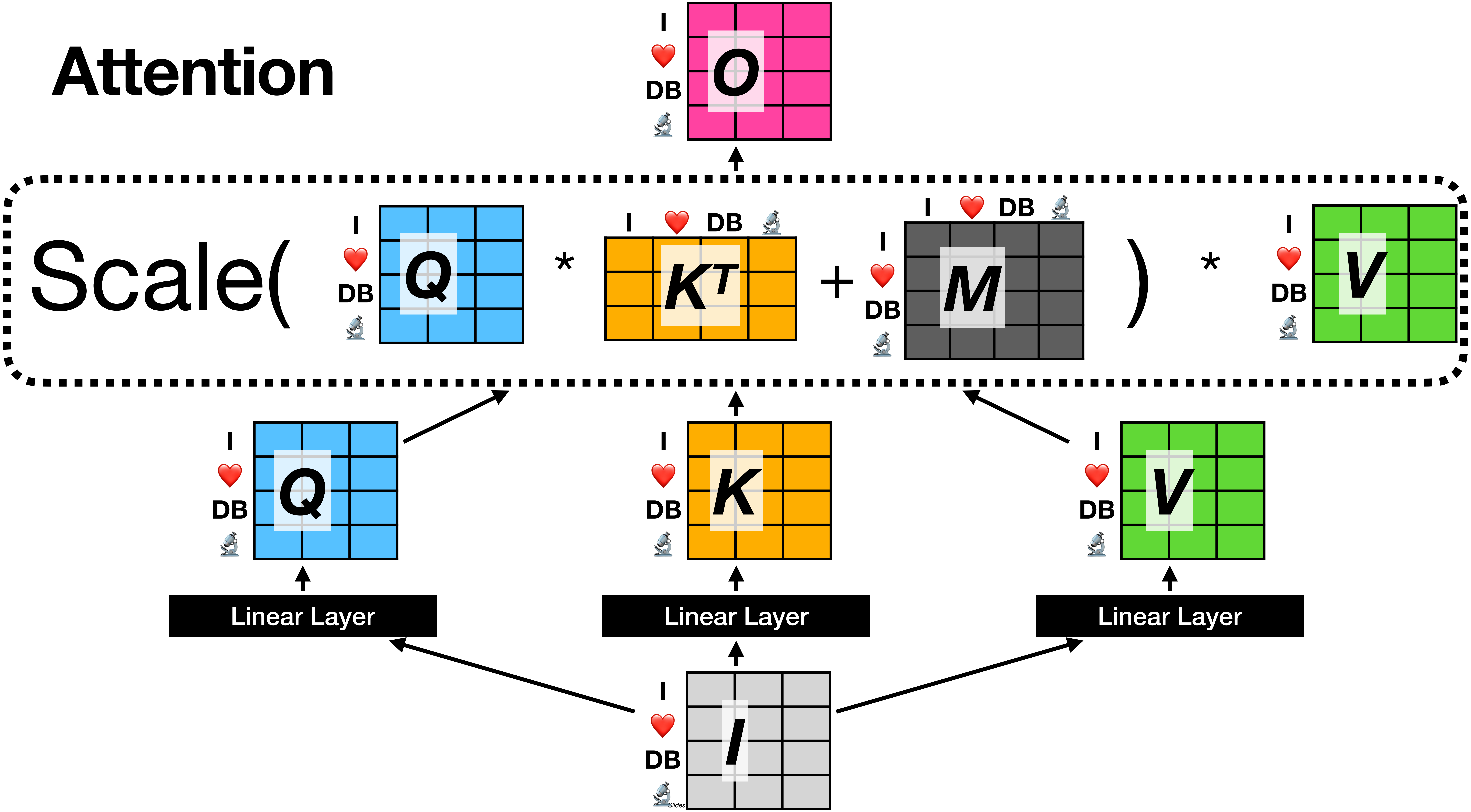
Scale(
I
DB
Q
*
I
DB
K^T
+
I
DB
M
)
I
DB
Q
I
DB
K
I
DB
V
Linear Layer
Linear Layer
Linear Layer
I
DB
I

Attention



Scale(
I
DB
Q
*
I
DB
KT
+
I
DB
I
DB
M
)
*
I
DB
V
I
DB
Q
I
DB
K
I
DB
V
Linear Layer
Linear Layer
Linear Layer
I
DB
I

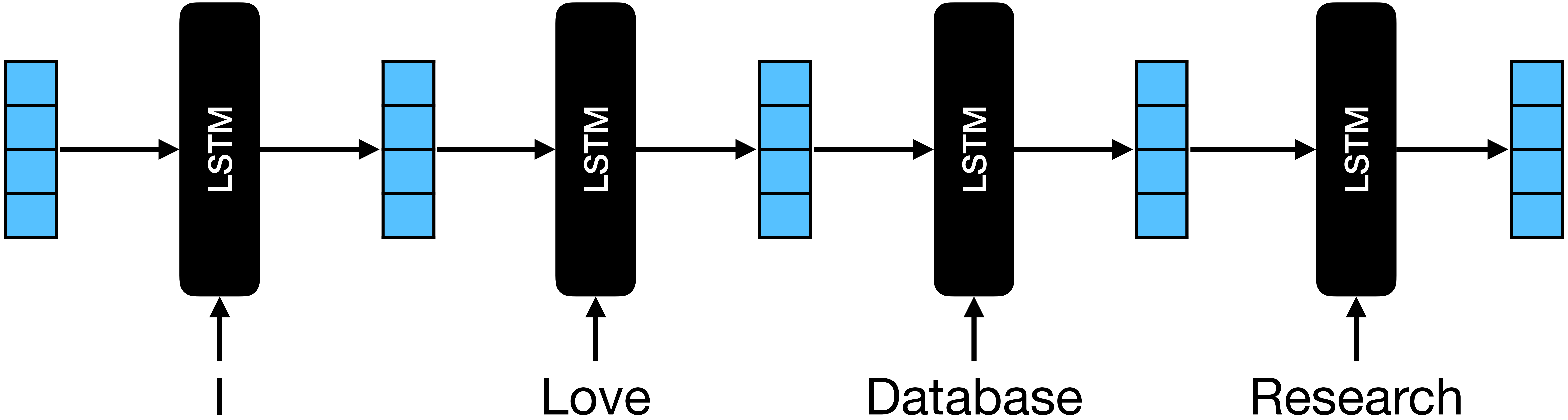
Attention


O
Scale(
Q
*
K^T
+
M
)
*
V
I
DB
Linear Layer
Linear Layer
Linear Layer
Q
K
V
I

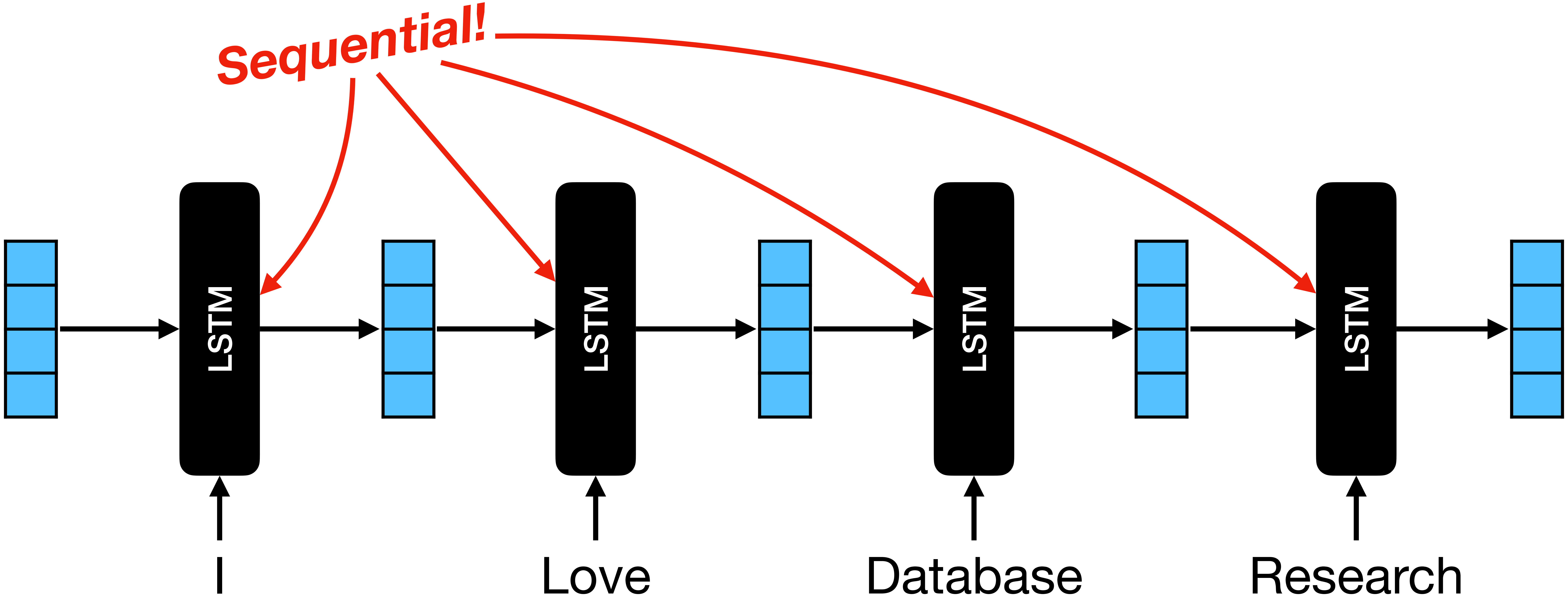
Demo: Visualizing Attention

https://colab.research.google.com/drive/1DG2h6uakCsSVmU0Vem0E5qUGWeADTqe5

Recurrent Neural Network



Recurrent Neural Network



Attention versus Recurrence

d: Vector dimension
n: Sequence length

Layer Type	Complexity per Layer
Self-Attention	$O(n^2 * d)$
Recurrent	$O(n * d^2)$

Attention versus Recurrence

d: Vector dimension
n: Sequence length

Layer Type	Complexity per Layer
Self-Attention	$O(n^2*d)$
Recurrent	$O(n*d^2)$

Self-attention is ... **Faster if *d>n***

Attention versus Recurrence

d: Vector dimension
n: Sequence length

Layer Type	Complexity per Layer	Sequential Operations
Self-Attention	$O(n^2*d)$	$O(1)$
Recurrent	$O(n*d^2)$	$O(n)$

Self-attention is ... **Faster if *d>n***

Attention versus Recurrence

d: Vector dimension
n: Sequence length

Layer Type	Complexity per Layer	Sequential Operations
Self-Attention	$O(n^2 * d)$	$O(1)$
Recurrent	$O(n * d^2)$	$O(n)$

Self-attention is ... **Faster if *d*>*n*** **More parallelizable**

Attention versus Recurrence

d: Vector dimension
n: Sequence length

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 * d)$	$O(1)$	$O(1)$
Recurrent	$O(n * d^2)$	$O(n)$	$O(n)$

Self-attention is ... **Faster if *d>n*** **More parallelizable**

Attention versus Recurrence

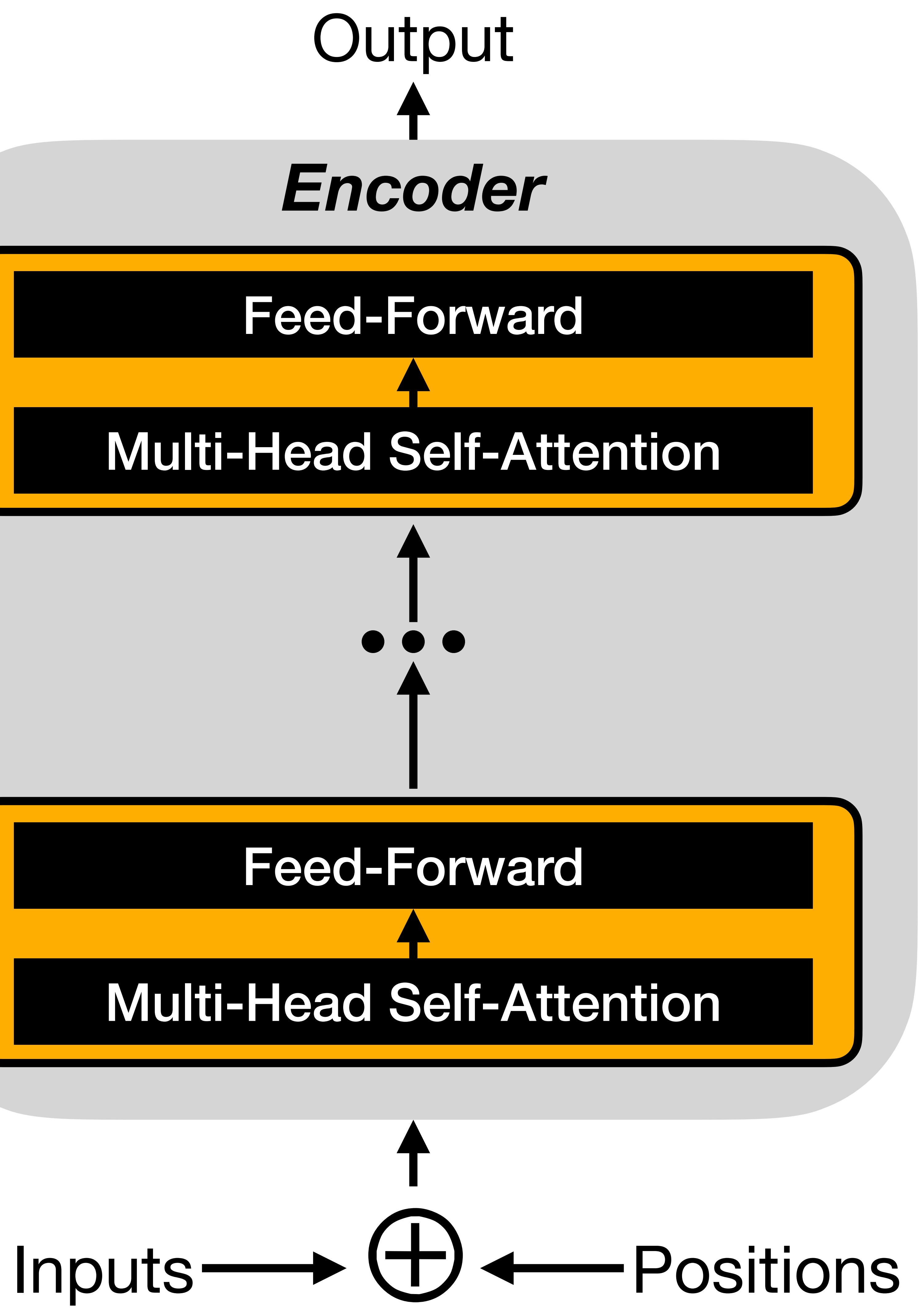
d: Vector dimension
n: Sequence length

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2*d)$	$O(1)$	$O(1)$
Recurrent	$O(n*d^2)$	$O(n)$	$O(n)$

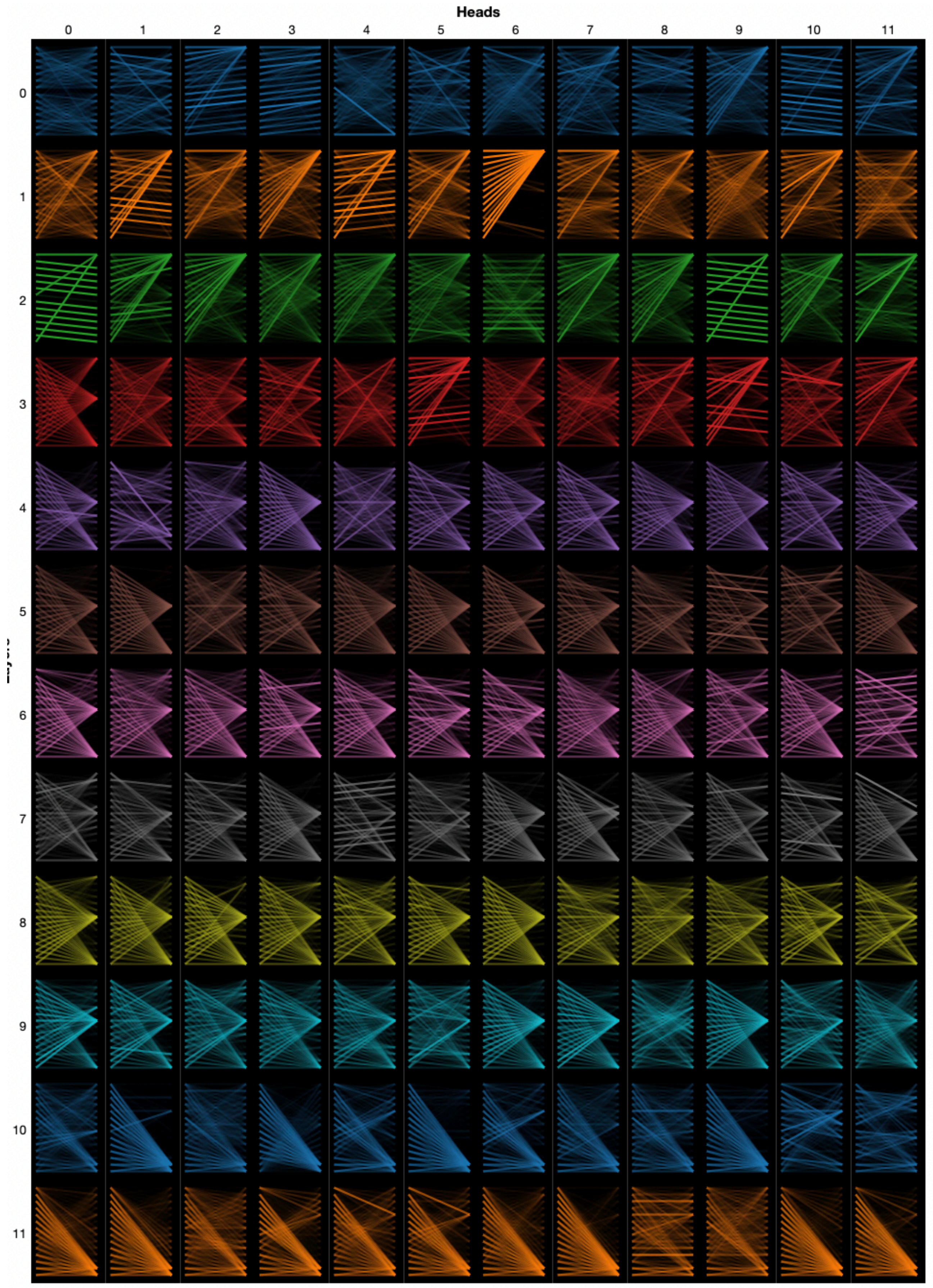
Self-attention is ... **Faster if *d>n*** **More parallelizable** **Easier to learn**

The Transformer

(Details omitted: skip connections, layer normalization, masking)

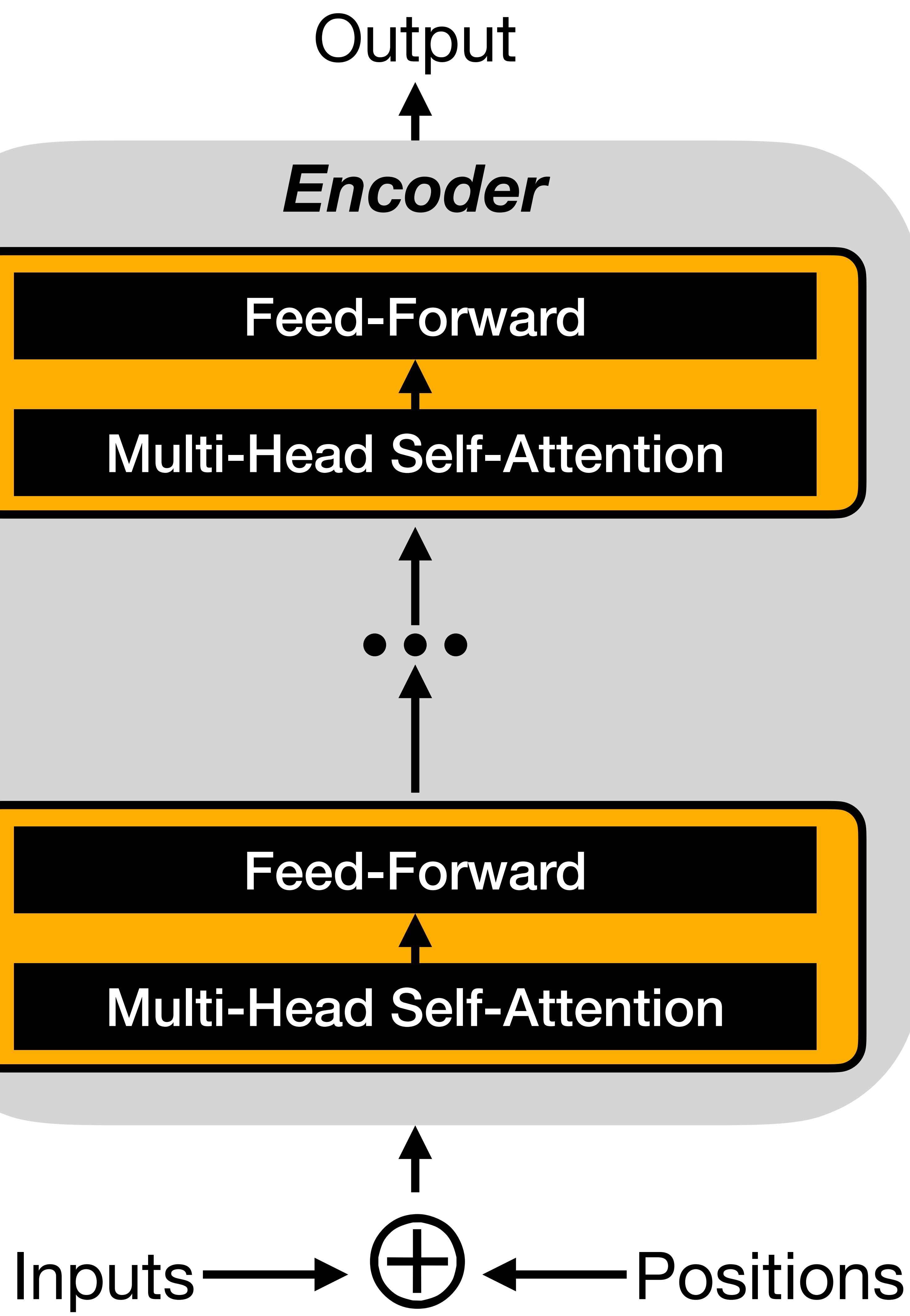


Multi-Head, Multi-Layer Attention Visualization



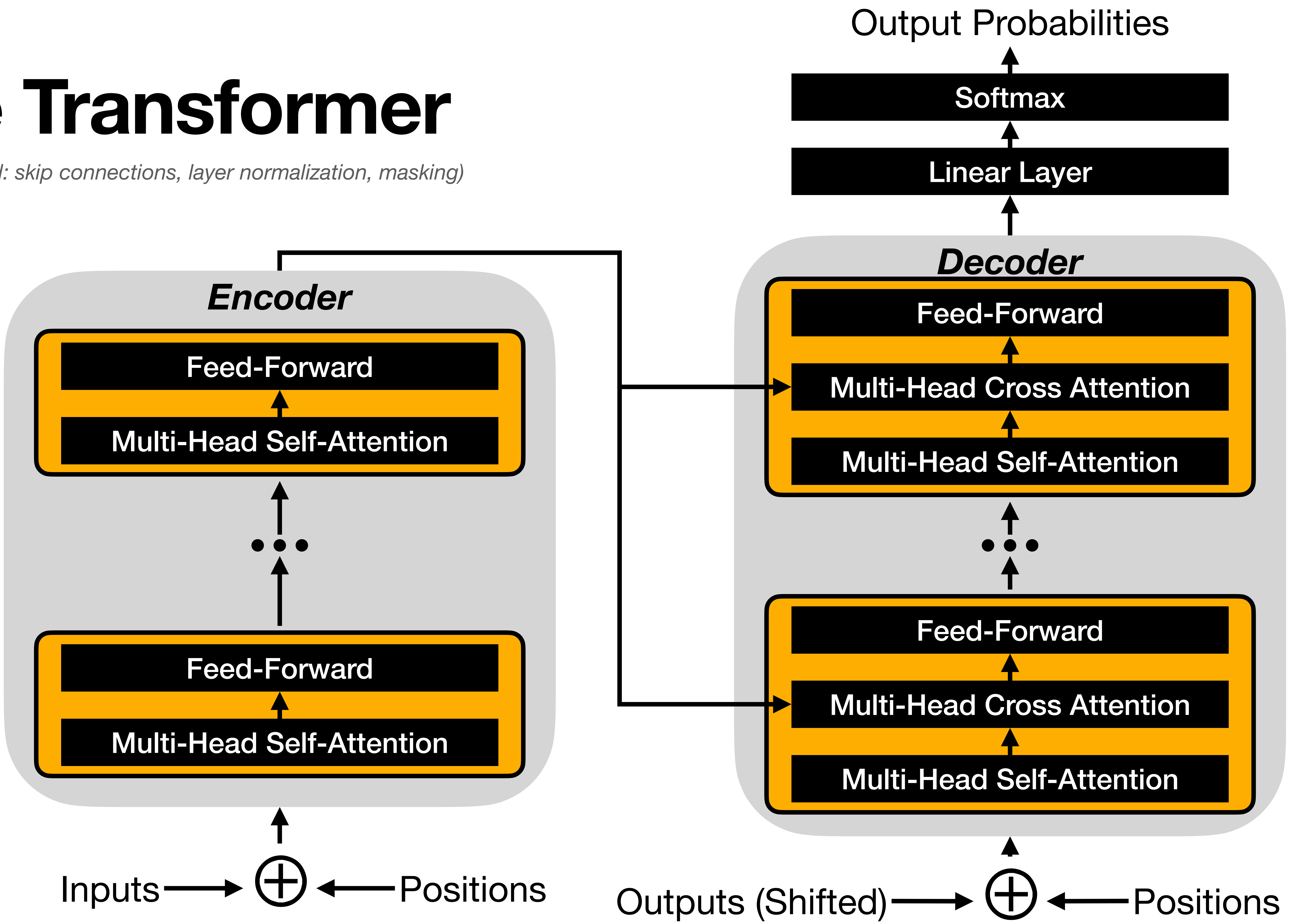
The Transformer

(Details omitted: skip connections, layer normalization, masking)



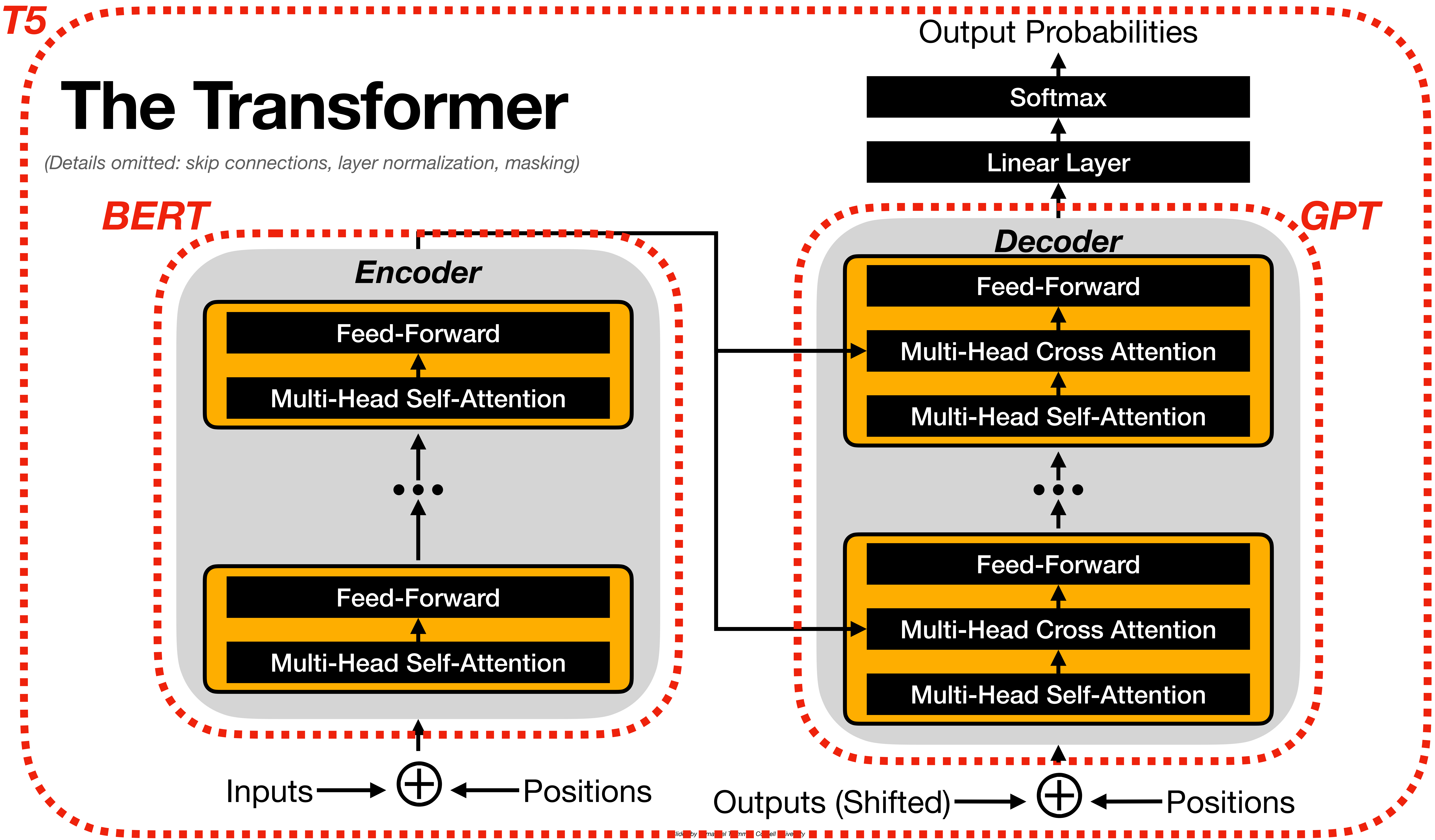
The Transformer

(Details omitted: skip connections, layer normalization, masking)



The Transformer

(Details omitted: skip connections, layer normalization, masking)



?

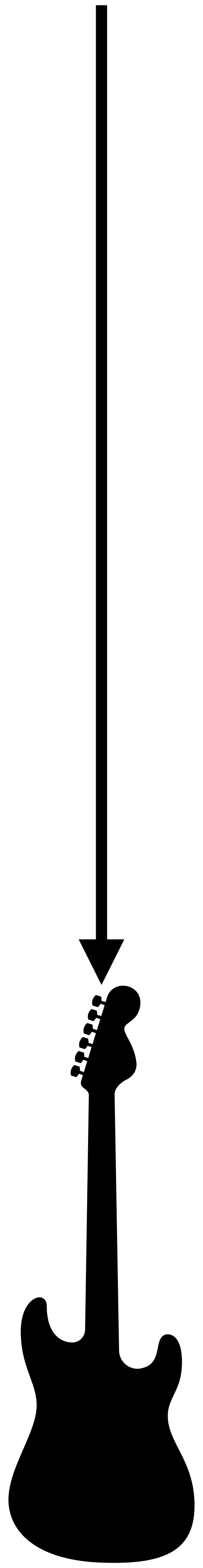
Transfer Learning

Transfer Learning: Idea

Untrained

Transfer Learning: Idea

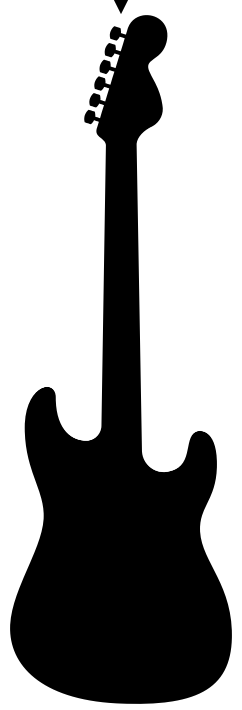
Untrained



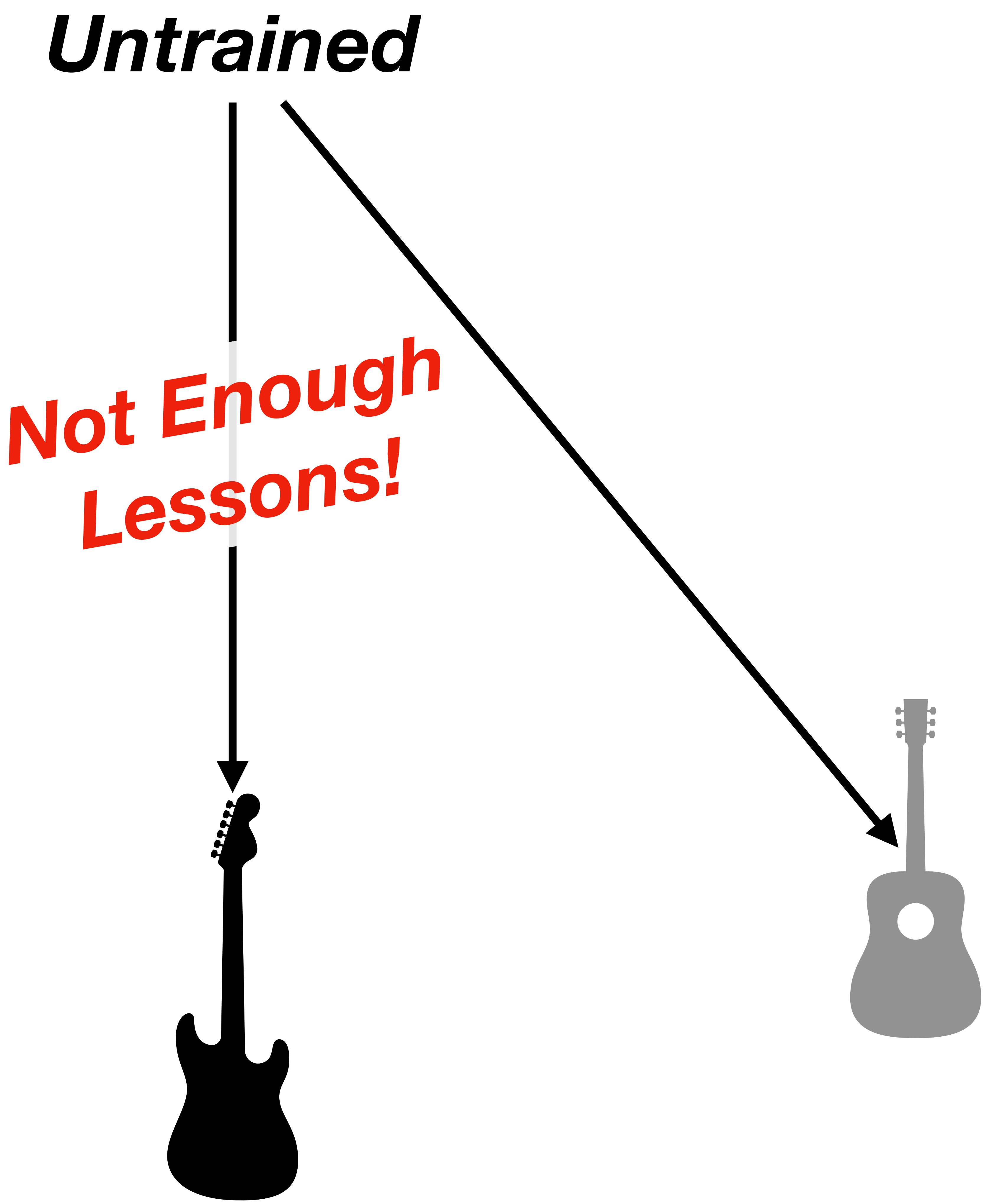
Transfer Learning: Idea

Untrained

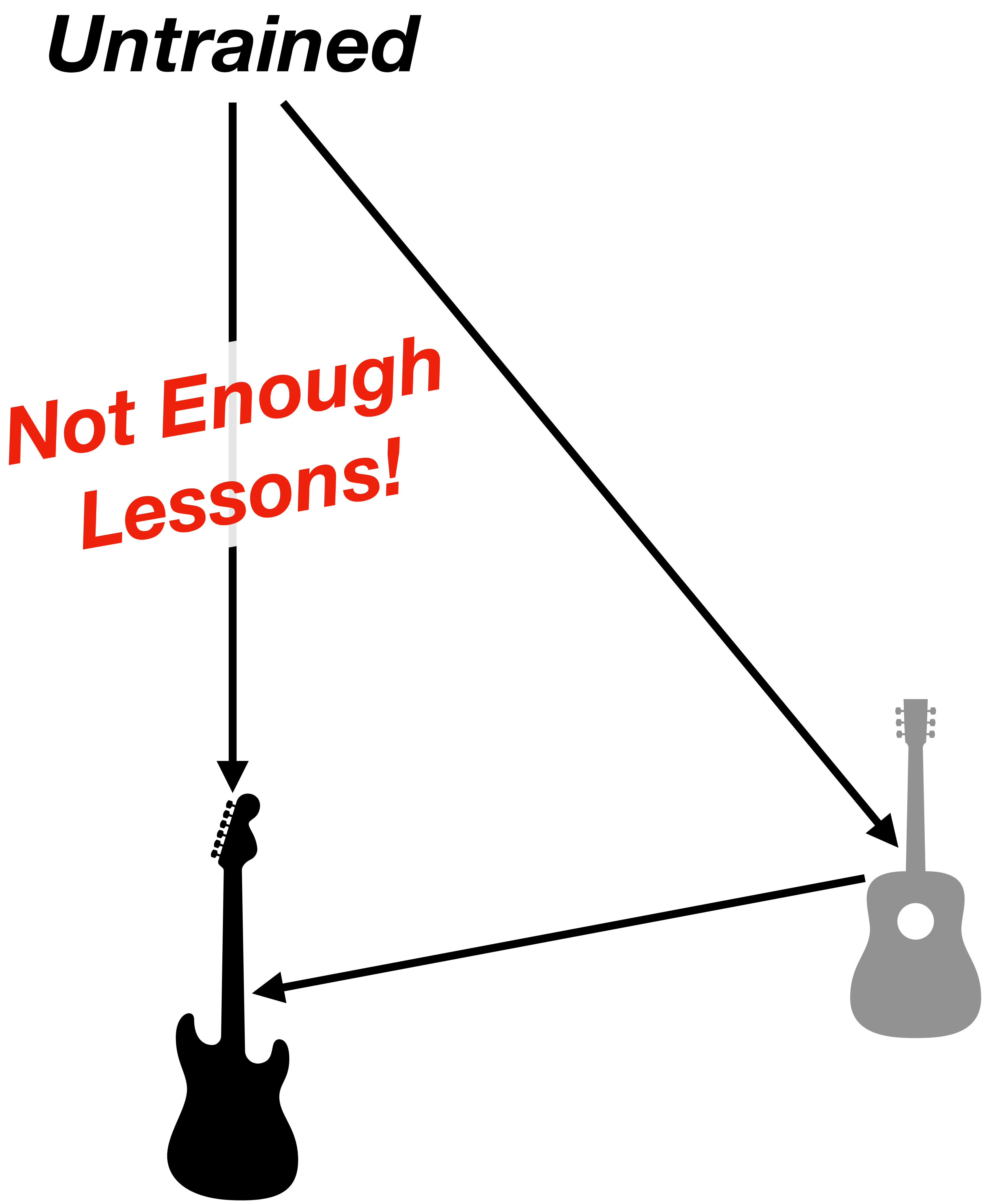
Not Enough Lessons!



Transfer Learning: Idea



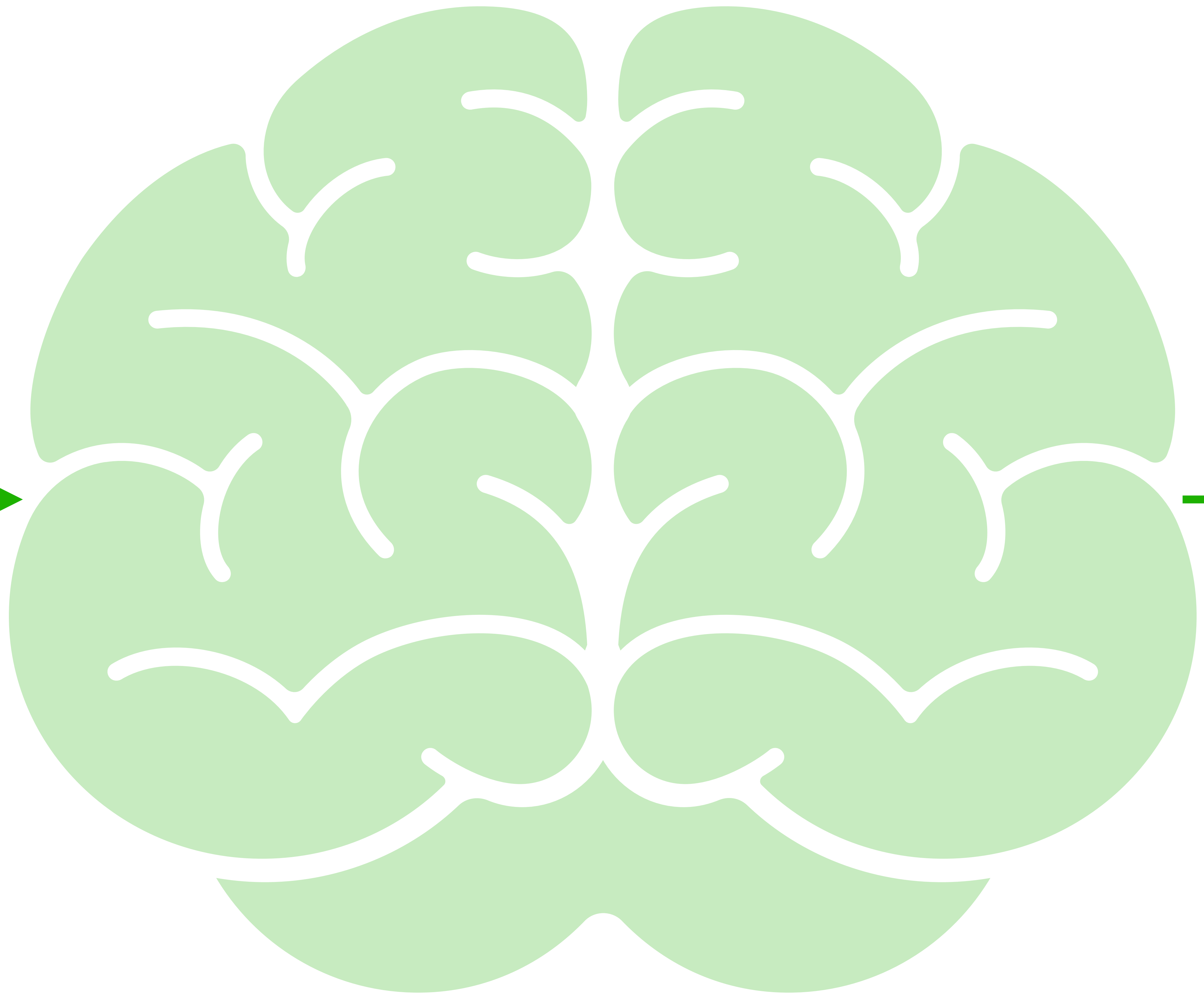
Transfer Learning: Idea



Transfer Learning: Idea

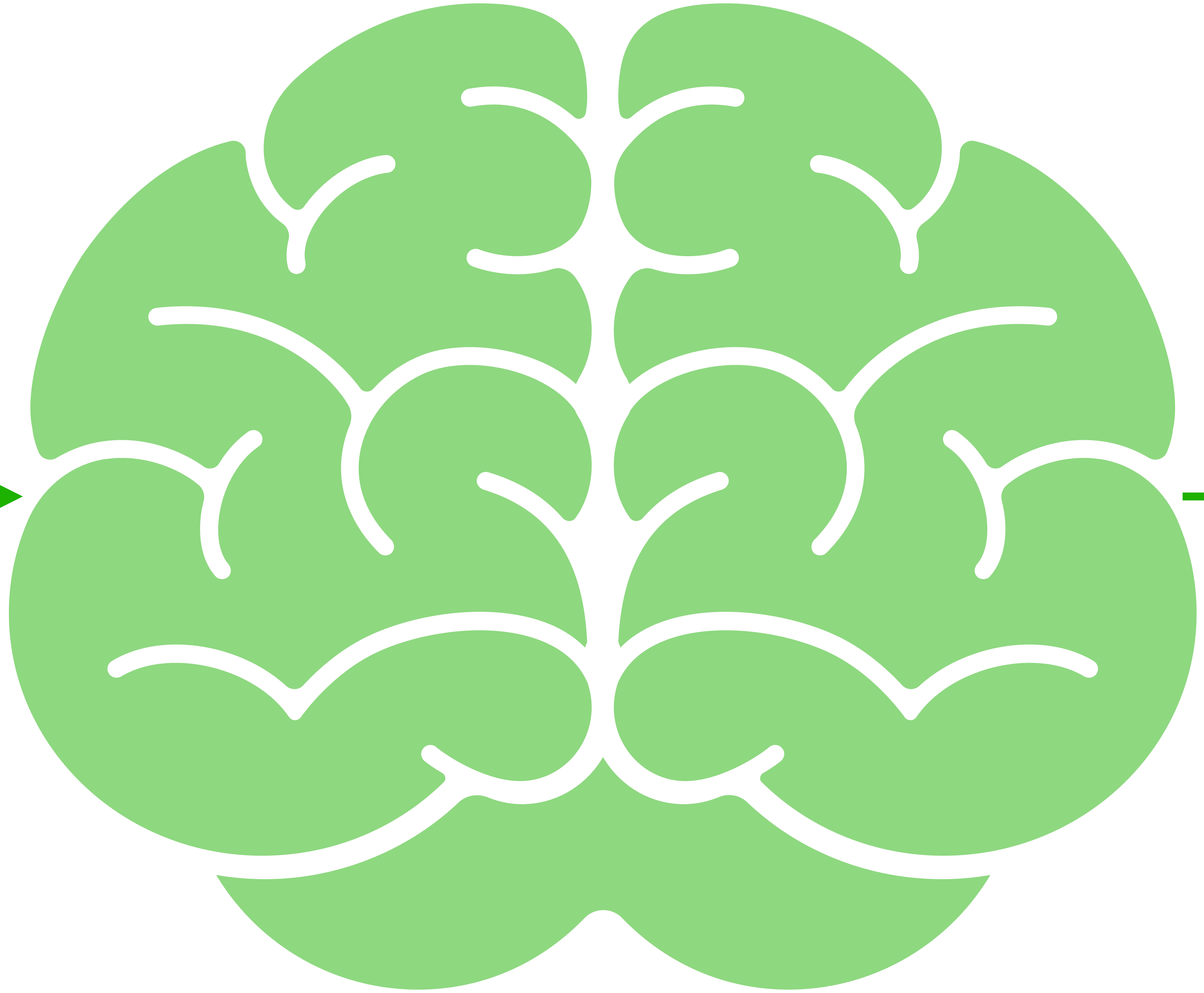
Pre-Training

Pre-Training

Lorem ... →  → ... Ipsum

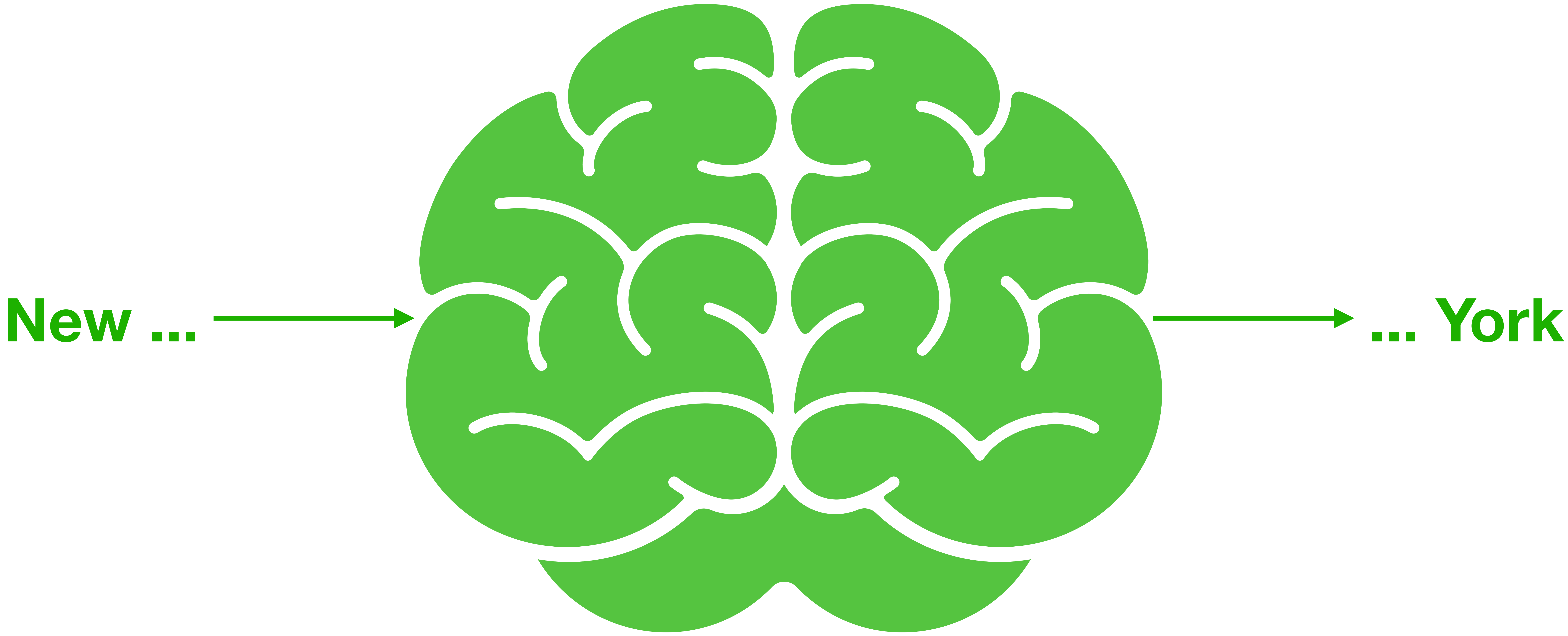
Pre-Training

Marco ...



... Polo

Pre-Training

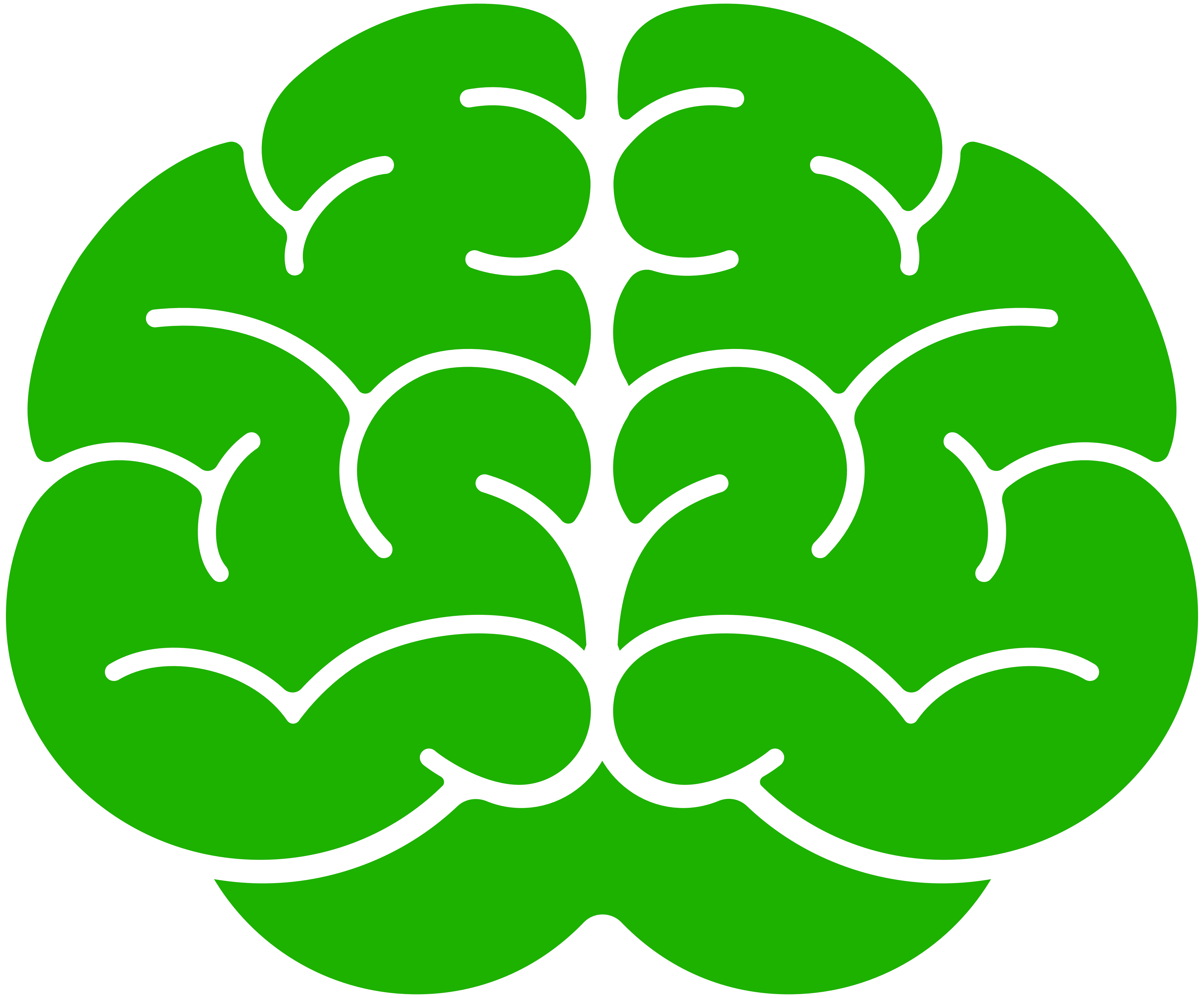


Pre-Training

Big ...

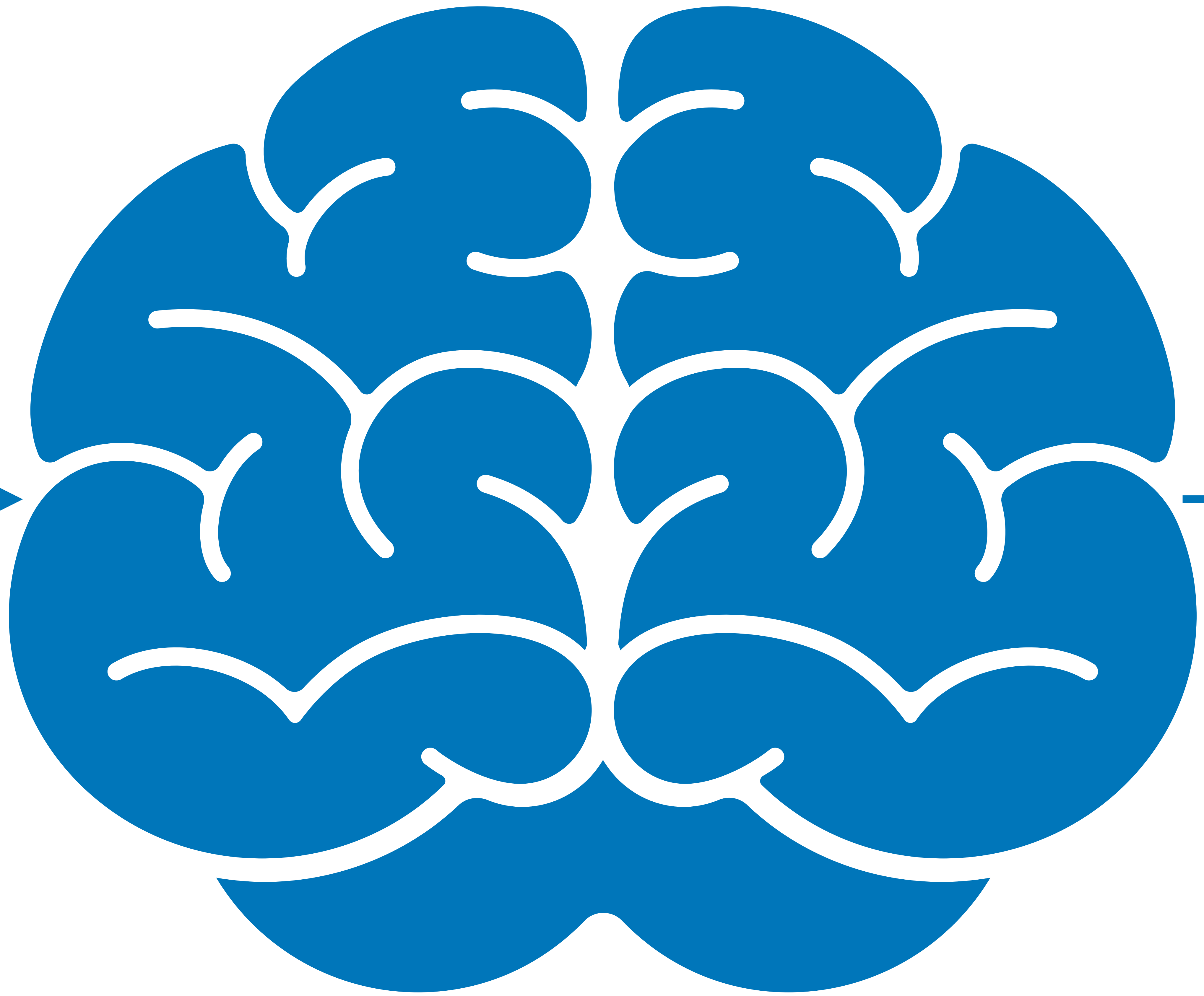
... Data

Pre-Training



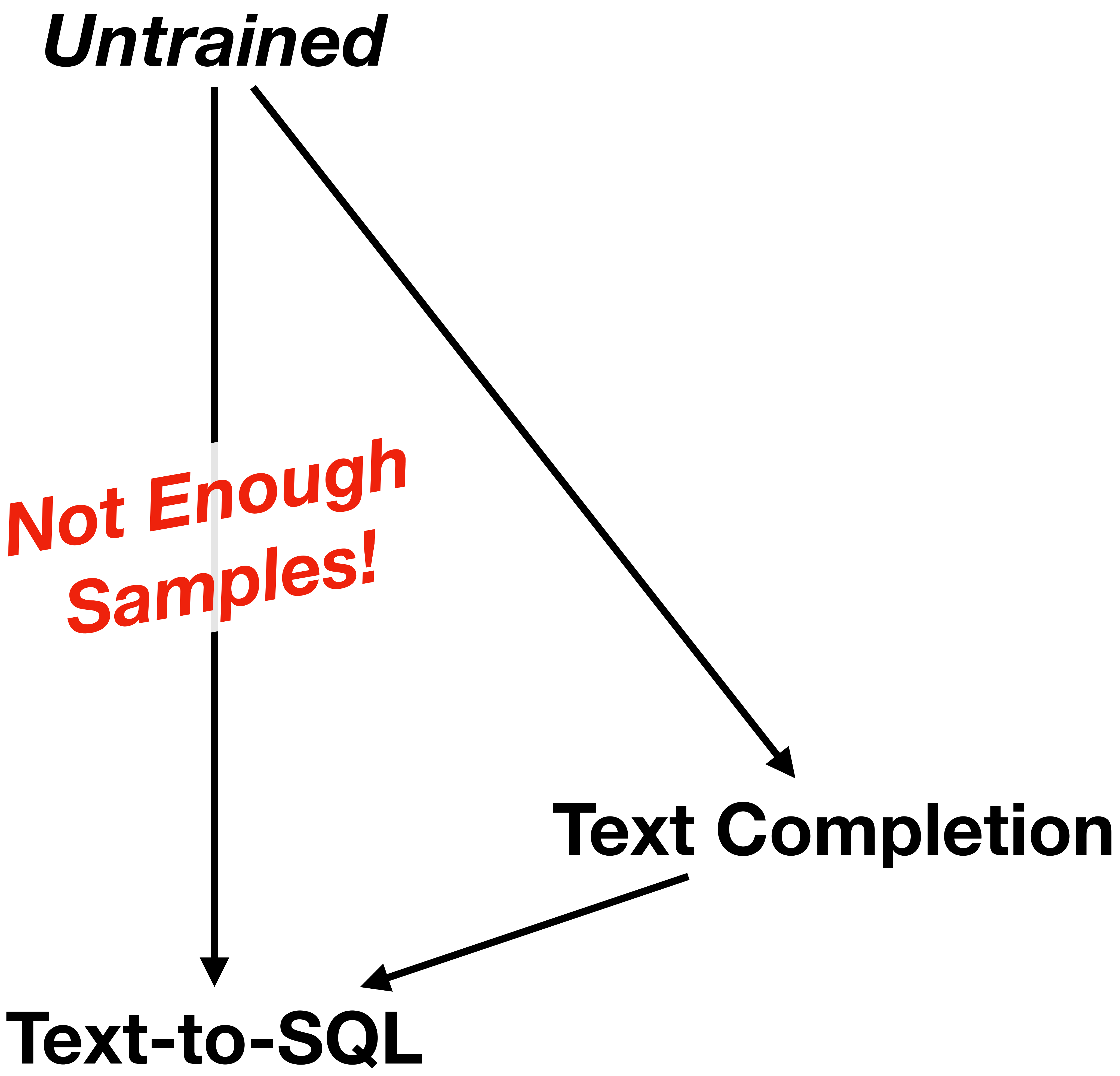
Fine-Tuning

How many customers?



SELECT Count(*) FROM Customer

Transfer Learning: Idea



Pre-Training Objectives

Objective	Description	Examples
Masked Language Modeling	Predict obfuscated words	BERT
Causal Language Modeling	Predict next word	GPT
Denoising Objective	Correct text with noise	BART

Quantifying Advantages

Universal Language Model Fine-tuning for Text Classification

Jeremy Howard*
fast.ai
University of San Francisco
j@fast.ai

Sebastian Ruder*
Insight Centre, NUI Galway
Aylien Ltd., Dublin
sebastian@ruder.io

Abstract

Inductive transfer learning has greatly impacted computer vision, but existing approaches in NLP still require task-specific

While Deep Learning models have achieved state-of-the-art on many NLP tasks, these models are trained from scratch, requiring large datasets, and days to converge. Research in NLP focused mostly on *transductive* transfer (Blitzer et al.,

Quantifying Advantages

... with only 100 labeled examples, it matches the performance of training from scratch on 100x more data

Universal Language Model Fine-tuning for Text Classification

Jeremy Howard*
fast.ai
University of San Francisco
j@fast.ai

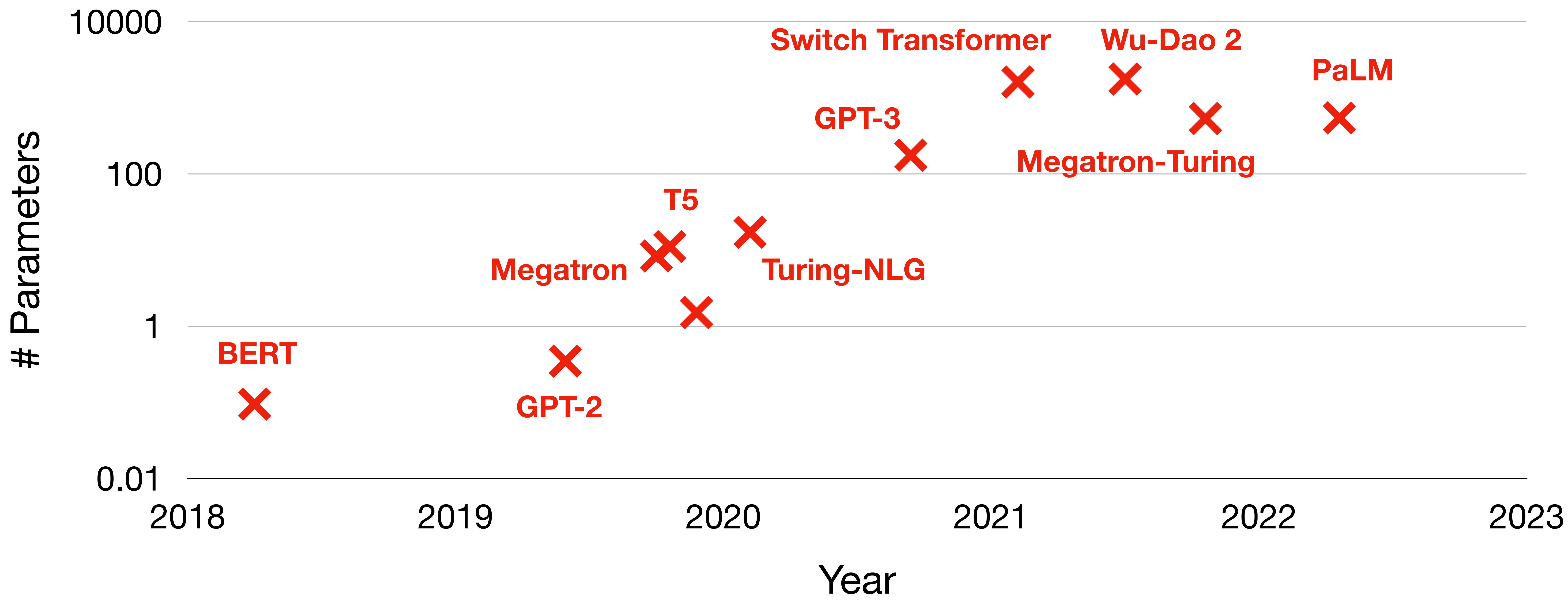
Sebastian Ruder*
Insight Centre, NUI Galway
Aylien Ltd., Dublin
sebastian@ruder.io

Abstract

Inductive transfer learning has greatly impacted computer vision, but existing approaches in NLP still require task-specific

While Deep Learning models have achieved state-of-the-art on many NLP tasks, these models are trained from scratch, requiring large datasets, and days to converge. Research in NLP focused mostly on *transductive* transfer (Blitzer et al.,

Evolution of Language Models



Language Models are Few-Shot Learners

Tom B. Brown* Benjamin Mann* Nick Ryder* Melanie Subbiah*

Jared Kaplan† Prafulla Dhariwal Arvind Neelakantan Pranav Shyam

Girish Sastry Amanda Askell Sandhini Agarwal Ariel Herbert-Voss

Gretchen Krueger Tom Henighan Rewon Child Aditya Ramesh

Daniel M. Ziegler Jeffrey Wu Clemens Winter

Christopher Hesse Mark Chen Eric Sigler Mateusz Litwin Scott Gray

Benjamin Chess Jack Clark Christopher Berner

Sam McCandlish Alec Radford Ilya Sutskever Dario Amodei

Abstract

We demonstrate that scaling up language models greatly improves task-agnostic, few-shot performance, sometimes even becoming competitive with prior state-of-

Language Models are Few-Shot Learners

Tom B. Brown* **Benjamin Mann*** **Nick Ryder*** **Melanie Subbiah***

Jared Kaplan† **Prafulla Dhariwal** **Arvind Neelakantan** **Pranav Shyam**

Girish Sastry **Amanda Askell** **Sandhini Agarwal** **Ariel Herbert-Voss**

Gretchen Krueger **Tom Henighan** **Rewon Child** **Aditya Ramesh**

Daniel M. Ziegler **Jeffrey Wu** **Clemens Winter**

Christopher Hesse **Mark Chen** **Eric Sigler** **Mateusz Litwin** **Scott Gray**

Benjamin Chess **Jack Clark** **Christopher Berner**

Sam McCandlish **Alec Radford** **Ilya Sutskever** **Dario Amodei**

Abstract

We demonstrate that scaling up language models greatly improves task-agnostic, few-shot performance, sometimes even becoming competitive with prior state-of-

Prompting

- Describe task as text input
- **Zero-shot** learning
    - No samples are provided in input
- **Few-shot** learning
    - Few (typically up to ten) samples

Prompting

- Describe task as text input
- **Zero-shot** learning
  - No samples are provided in input
- **Few-shot** learning
  - Few (typically up to ten) samples

Prompt Formulation Matters!

?

Libraries and Interfaces

Hugging Face (🤗) Transformers

https://huggingface.co/

GPT-3 by OpenAI

https://openai.com/api/

Applications to Data Management

Natural Language Engineering **1** (1): 29–81 © 1995 Cambridge University Press

Natural language interfaces to databases – an introduction

I. ANDROUTSOPOULOS, G.D. RITCHIE
Department of Artificial Intelligence, University of Edinburgh
80 South Bridge, Edinburgh EH1 1HN, Scotland, UK
e-mail: ion@aisb.ed.ac.uk, G.D.Ritchie@ed.ac.uk

P. THANISCH
Department of Computer Science, University of Edinburgh
King's Buildings, Mayfield Road, Edinburgh EH9 3JZ, Scotland, UK
e-mail: pt@dcs.ed.ac.uk

(*Received 25 June 1994; revised 10 December 1994*)

NaLIR: An Interactive Natural Language Interface for Querying Relational Databases*

Fei Li
Univ. of Michigan, Ann Arbor
lifei@umich.edu

H. V. Jagadish
Univ. of Michigan, Ann Arbor
jag@umich.edu

ABSTRACT

In this demo, we present NaLIR, a generic interactive natural language interface for querying relational databases. NaLIR can accept a logically complex English language sentence as query input. This query is first translated into a SQL query, which may include aggregation, nesting, and various types of joins, among other things, and then evaluated against an RDBMS. In this demonstration, we show that NaLIR, while far from being able to pass the Turing test, is perfectly usable in practice, and able to handle even quite complex queries in a variety of application domains. In addition, we also demonstrate how carefully designed interactive communication can avoid misinterpretation with minimum user burden.

Categories and Subject Descriptors

natural language queries is often regarded as the ultimate goal for a database query interface.

However, progress has been slow, even as general Natural Language Processing systems have improved over the years. We believe this is primarily due to the difficulty of translating user-specified query structure to the actual schema structure in the database. By addressing this challenge, we believe we have removed the greatest barrier in natural language querying of databases.

In this demo, we describe NaLIR, a generic interactive natural language interface for querying relational databases. In NaLIR, an arbitrary English language sentence, which can be quite complex in logic, is taken as query input. This query is first translated into a SQL query, which may contain aggregation, nesting, and various types of joins, among other things. Then, an RDBMS is used to evaluate the translated SQL query and return the results to the user. For exam-

Rank	Model	Test
1 Sep 1, 2022	SHiP+PICARD (DB content used) *Anonymous*	**76.6**
2 Jun 4, 2022	RASAT+PICARD (DB content used) *Anonymous*	75.5
3 May 8, 2022	T5-SR (DB content used) *Anonymous*	75.2
4 Aug 12, 2022	RESDSQL+T5-1.1-lm100k-xl (DB content used) *Anonymous*	75.1
4 Jul 14, 2021	T5-3B+PICARD (DB content used) *Element AI, a ServiceNow company* (Scholak et al., EMNLP'21) code	75.1
6 Aug 12, 2022	RESDSQL+T5-1.1-lm100k-large (DB content used) *Anonymous*	74.8
7 May 18, 2022	SeaD + SP (DB content used) *Anonymous*	74.1
8 May 4, 2021	RATSQL+GAP+NatSQL (DB content used) *Queen Mary University of London* (Gan et al., EMNLP Findings'21) code	73.3
9 Mar 10, 2021	SmBoP + GraPPa (DB content used) *Tel-Aviv University & Allen Institute for AI* (Rubin and Berant, NAACL'21) code	71.1
10 Aug 05, 2021	RaSaP + ELECTRA (DB content used) *Ant Group, ZhiXiaoBao & Ada* (Huang et al.,'21)	70.0

Leaderboard of SPIDER benchmark

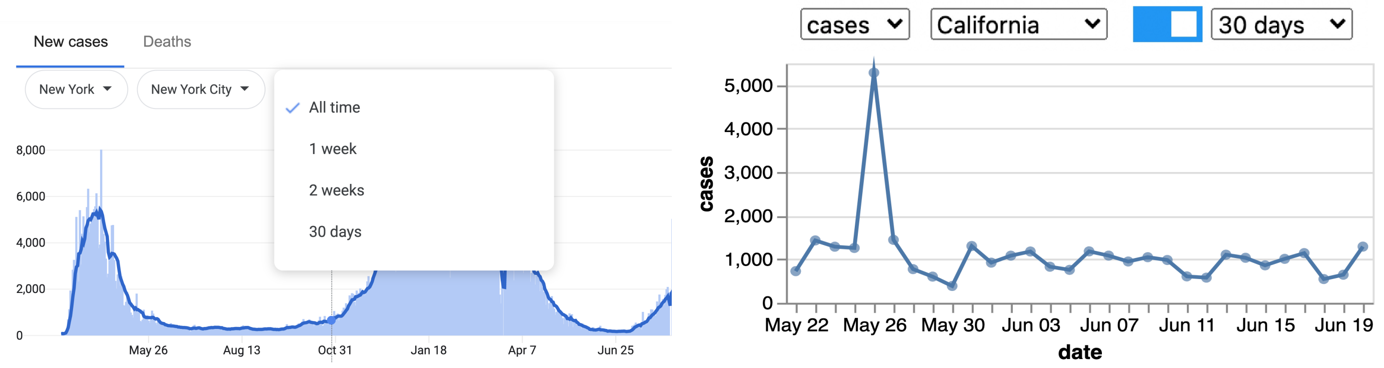
PI2: End-to-end Interactive Visualization Interface Generation from Queries

Yiru Chen
yiru.chen@columbia.edu
Columbia University
New York, NY, USA

Eugene Wu
ewu@cs.columbia.edu
Columbia University
New York, NY, USA

ABSTRACT

Interactive visualization interfaces are critical in data analysis. Yet creating new interfaces is challenging, as the developer must understand the queries needed for the desired analysis task, and then design the appropriate interface. Existing task models are too abstract to be used to automatically generate interfaces, and visualization recommenders do not take the queries nor interactions into account. PI2 is the first system to generate fully functional interactive visualization interfaces from a representative sequence of task queries. PI2 analyzes queries syntactically and proposes a novel DIFFTREE representation that encodes the systematic variations between query abstract syntax trees. PI2 then poses interface generation as a schema mapping problem from each DIFFTREE to a visualization that renders its results, and the variations encoded in each DIFFTREE to interactions in the interface. Interface generation further takes the layout and screen size into account. Our user studies show that PI2 interfaces are comparable to or better than those designed by developers, and that PI2 can generate ex-



(a) Google Covid Vis (b) This paper: PI2

(c) PI

Figure 1: (a) Google’s Covid-19 visualization. Using queries in Listing 1, interfaces generated by (b) this paper (PI2) and (c) prior work (PI).

1 INTRODUCTION

we fine-tuned a recent NL-to-SQL language model ... using 50 manually annotated ... examples

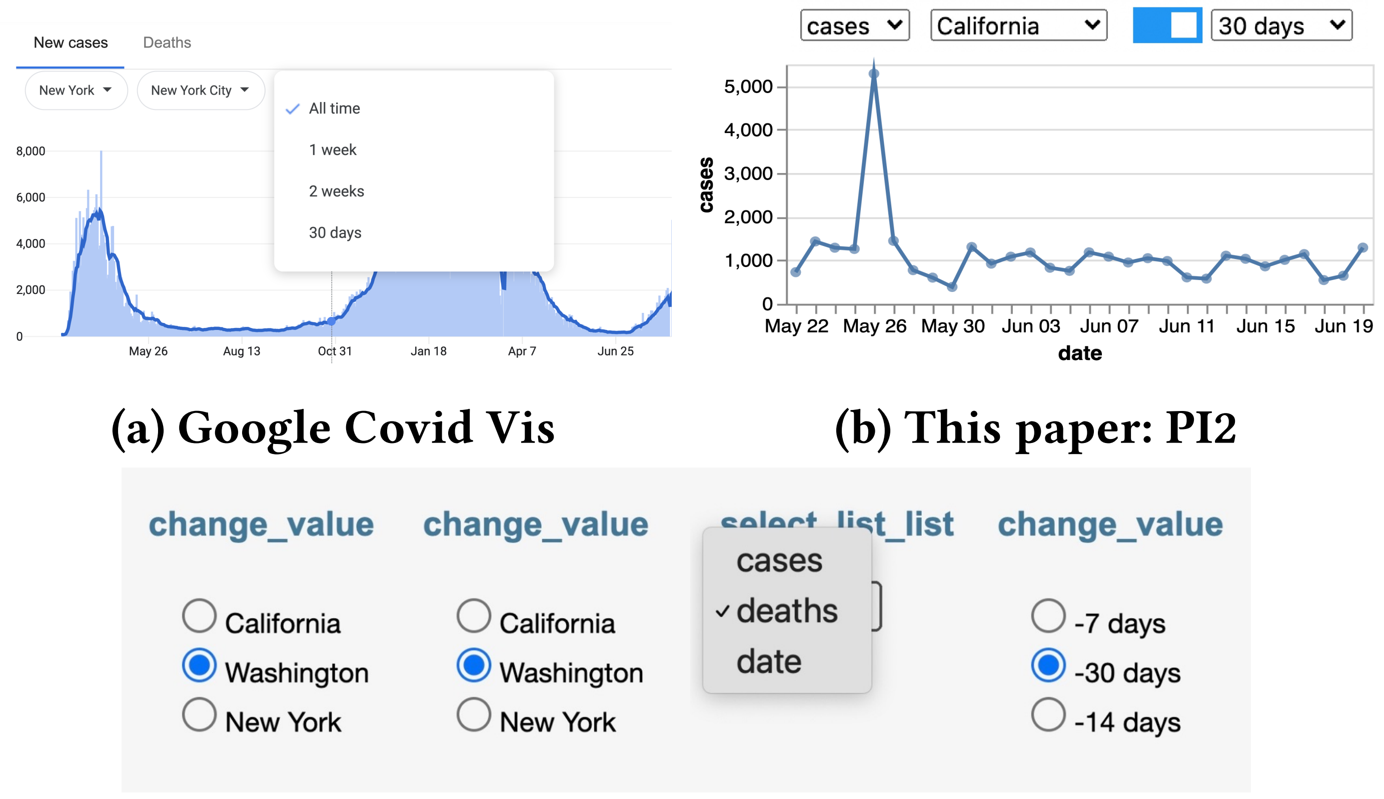
PI2: End-to-end Interactive Visualization Interface Generation from Queries

Yiru Chen
yiru.chen@columbia.edu
Columbia University
New York, NY, USA

Eugene Wu
ewu@cs.columbia.edu
Columbia University
New York, NY, USA

ABSTRACT

Interactive visualization interfaces are critical in data analysis. Yet creating new interfaces is challenging, as the developer must understand the queries needed for the desired analysis task, and then design the appropriate interface. Existing task models are too abstract to be used to automatically generate interfaces, and visualization recommenders do not take the queries nor interactions into account. PI2 is the first system to generate fully functional interactive visualization interfaces from a representative sequence of task queries. PI2 analyzes queries syntactically and proposes a novel DIFFTREE representation that encodes the systematic variations between query abstract syntax trees. PI2 then poses interface generation as a schema mapping problem from each DIFFTREE to a visualization that renders its results, and the variations encoded in each DIFFTREE to interactions in the interface. Interface generation further takes the layout and screen size into account. Our user studies show that PI2 interfaces are comparable to or better than those designed by developers, and that PI2 can generate ex-



(a) Google Covid Vis (b) This paper: PI2

(c) PI

Figure 1: (a) Google's Covid-19 visualization. Using queries in Listing 1, interfaces generated by (b) this paper (PI2) and (c) prior work (PI).

1 INTRODUCTION

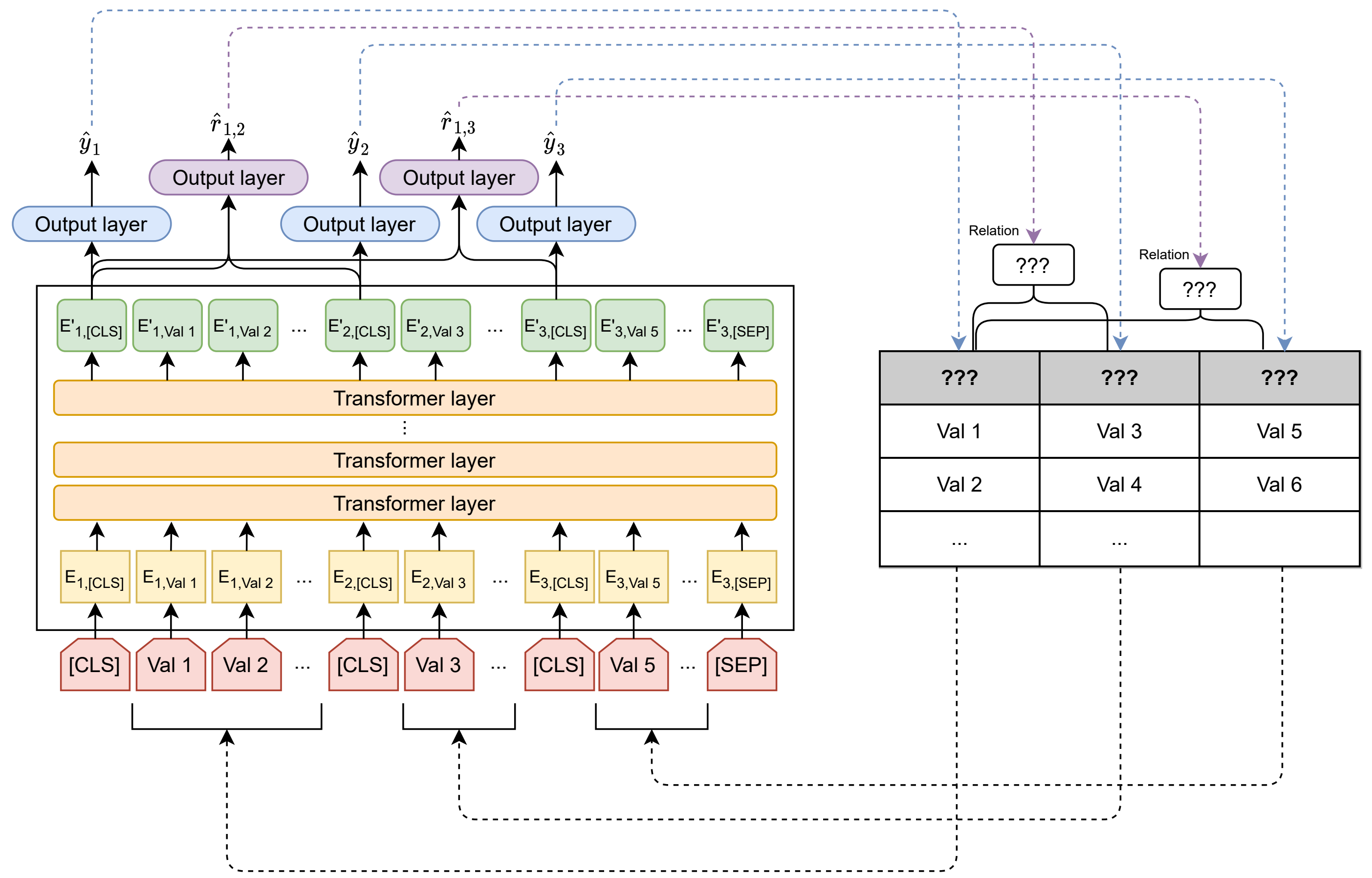
Annotating Columns with Pre-trained Language Models

Yoshihiko Suhara, Jinfeng Li,
Yuliang Li, Dan Zhang
Megagon Labs
{yoshi,jinfeng,yuliang,dan_z}@megagon.ai

Çağatay Demiralp*
Sigma Computing
cagatay@sigmacomputing.com

Chen Chen†
Megagon Labs
chen@megagon.ai

Wang-Chiew Tan*
Meta AI
wangchiew@fb.com



ABSTRACT

Inferring meta information about tables, such as column headers or relationships between columns, is an active research topic in data management as we find many tables are missing some of this information. In this paper, we study the problem of annotating table columns (i.e., predicting column types and the relationships between columns) using only information from the table itself. We develop a multi-task learning framework (called Doduo) based on pre-trained language models, which takes the entire table as input and predicts column types/relations using a single model. Experimental results show that Doduo establishes new state-of-the-art performance on two benchmarks for the column type prediction and column relation prediction tasks with up to 4.0% and 11.9% improvements, respectively. We report that Doduo can already

Creating Embeddings of Heterogeneous Relational Datasets for Data Integration Tasks

Riccardo Cappuzzo
cappuzzo@eurecom.fr
EURECOM

Paolo Papotti
papotti@eurecom.fr
EURECOM

Saravanan Thirumuruganathan
sthirumuruganathan@hbku.edu.qa
QCRI, HBKU

ABSTRACT

Deep learning based techniques have been recently used with promising results for data integration problems. Some methods directly use *pre-trained* embeddings that were trained on a large corpus such as Wikipedia. However, they may not always be an appropriate choice for enterprise datasets with custom vocabulary. Other methods adapt techniques from natural language processing to obtain embeddings for the enterprise's relational data. However, this approach blindly treats a tuple as a sentence, thus losing a large amount of contextual information present in the tuple.

We propose algorithms for obtaining *local embeddings* that are effective for data integration tasks on relational databases. We make four major contributions. First, we de-

CCS CONCEPTS

• **Theory of computation → Data integration**;

KEYWORDS

data integration; embeddings; deep learning; schema matching; entity resolution

ACM Reference Format:

Riccardo Cappuzzo, Paolo Papotti, and Saravanan Thirumuruganathan. 2020. Creating Embeddings of Heterogeneous Relational Datasets for Data Integration Tasks . In *Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data (SIGMOD'20), June 14–19, 2020, Portland, OR, USA.* ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/3318464.3389742

2021 IEEE 37th International Conference on Data Engineering (ICDE)

Valentine: Evaluating Matching Techniques for Dataset Discovery

Christos Koutras[1] George Siachamis[1,2] Andra Ionescu[1] Kyriakos Psarakis[1] Jerry Brons[2]
Marios Fragkoulis[1] Christoph Lofi[1] Angela Bonifati[3] Asterios Katsifodimos[1]

[1]*Delft Univeristy of Technology* [2]*ING Bank Netherlands* [3]*Lyon 1 University*

81-9184-3/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICDE51399.2021.00047

***Abstract*—Data scientists today search large data lakes to discover and integrate datasets. In order to bring together disparate data sources, dataset discovery methods rely on some form of schema matching: the process of establishing correspondences between datasets. Traditionally, schema matching has been used to find matching pairs of columns between a source and a target schema. However, the use of schema matching in dataset discovery methods differs from its original use. Nowadays schema matching serves as a building block for indicating and ranking inter-dataset relationships. Surprisingly, although a discovery method's success relies highly on the quality of the underlying matching algorithms, the latest discovery methods employ existing schema matching algorithms in an ad-hoc fashion due to the lack of openly-available datasets with ground truth, reference method implementations, and evaluation metrics.**

In this paper, we aim to rectify the problem of evaluating the effectiveness and efficiency of schema matching methods for

models [10], [11], and iii) finding similar tables to a given one using different similarity measures [7], [8].

The majority of these methods are based on a common, very critical component: *schema matching*, i.e., capturing relationships between elements of different schemata. In the case of tabular data, dataset discovery methods typically use schema matching techniques to automatically determine whether two columns (or even entire tables) are joinable or unionable. Since dataset discovery methods exploit relatedness information about a given set of datasets, the underlying matching technique of any data discovery method greatly affects its performance.

At the moment of writing, dataset discovery methods typically implement their own matcher, by combining or cus-

Deep Entity Matching with Pre-Trained Language Models

Yuliang Li, Jinfeng Li, Yoshihiko Suhara
Megagon Labs
{yuliang,jinfeng,yoshi}@megagon.ai

AnHai Doan
University of Wisconsin Madison
anhai@cs.wisc.edu

Wang-Chiew Tan
Megagon Labs
wangchiew@megagon.ai

ABSTRACT

We present DITTO, a novel entity matching system based on pre-trained Transformer-based language models. We fine-tune and cast EM as a sequence-pair classification problem to leverage such models with a simple architecture. Our experiments show that a straightforward application of language models such as BERT, DistilBERT, or RoBERTa pre-trained on large text corpora already significantly improves the matching quality and outperforms previous state-of-the-art (SOTA), by up to 29% of F1 score on benchmark datasets. We also developed three optimization techniques to further improve DITTO's matching capability. DITTO allows domain knowledge to be injected by highlighting important pieces of input information that may be of interest when making matching decisions. DITTO also summarizes strings that are too long so that only the essential information is retained and used for EM. Finally, DITTO adapts a SOTA technique on data augmentation for text to EM to augment the training data with (difficult) examples. This way, DITTO is forced to learn "harder" to improve the model's matching capability. The optimizations we developed further boost the performance

If the datasets are large, it can be expensive to determine the pairs of matching entries. For this reason, EM is typically accompanied by a pre-processing step, called *blocking*, to prune pairs of entries that are unlikely matches to reduce the number of candidate pairs to consider. As we will illustrate, correctly *matching* the candidate pairs requires substantial language understanding and domain-specific knowledge. Hence, entity matching remains a challenging task even for the most advanced EM solutions.

We present DITTO, a novel EM solution based on pre-trained Transformer-based language models (or *pre-trained language models* in short). We cast EM as a sequence-pair classification problem to leverage such models, which have been shown to generate highly contextualized embeddings that capture better language understanding compared to traditional word embeddings. DITTO further improves its matching capability through three optimizations: (1) It allows domain knowledge to be added by highlighting important pieces of the input that may be useful for matching decisions. (2) It summarizes long strings so that only the most essential information is retained and used for EM. (3) It augments training data with

Can Foundation Models Wrangle Your Data?

Avanika Narayan, Ines Chami†, Laurel Orr, Christopher Ré
Stanford University and †Numbers Station
{avanika,lorr1,chrismre}@cs.stanford.edu,ines.chami@numbersstation.ai

ABSTRACT

Foundation Models (FMs) are models trained on large corpora of data that, at very large scale, can generalize to new tasks without any task-specific finetuning. As these models continue to grow in size, innovations continue to push the boundaries of what these models can do on language and image tasks. This paper aims to understand an underexplored area of FMs: classical data tasks like cleaning and integration. As a proof-of-concept, we cast three data cleaning and integration tasks as prompting tasks and evaluate the performance of FMs on these tasks. We find that large FMs generalize and achieve SoTA performance on data cleaning and integration tasks, even though they are not trained for these data tasks. We identify specific research challenges and opportunities that these models present, including challenges with private and temporal data, and opportunities to make data driven systems more accessible to non-experts. We make our code and experiments publicly available at: https://github.com/HazyResearch/fm_data_tasks.

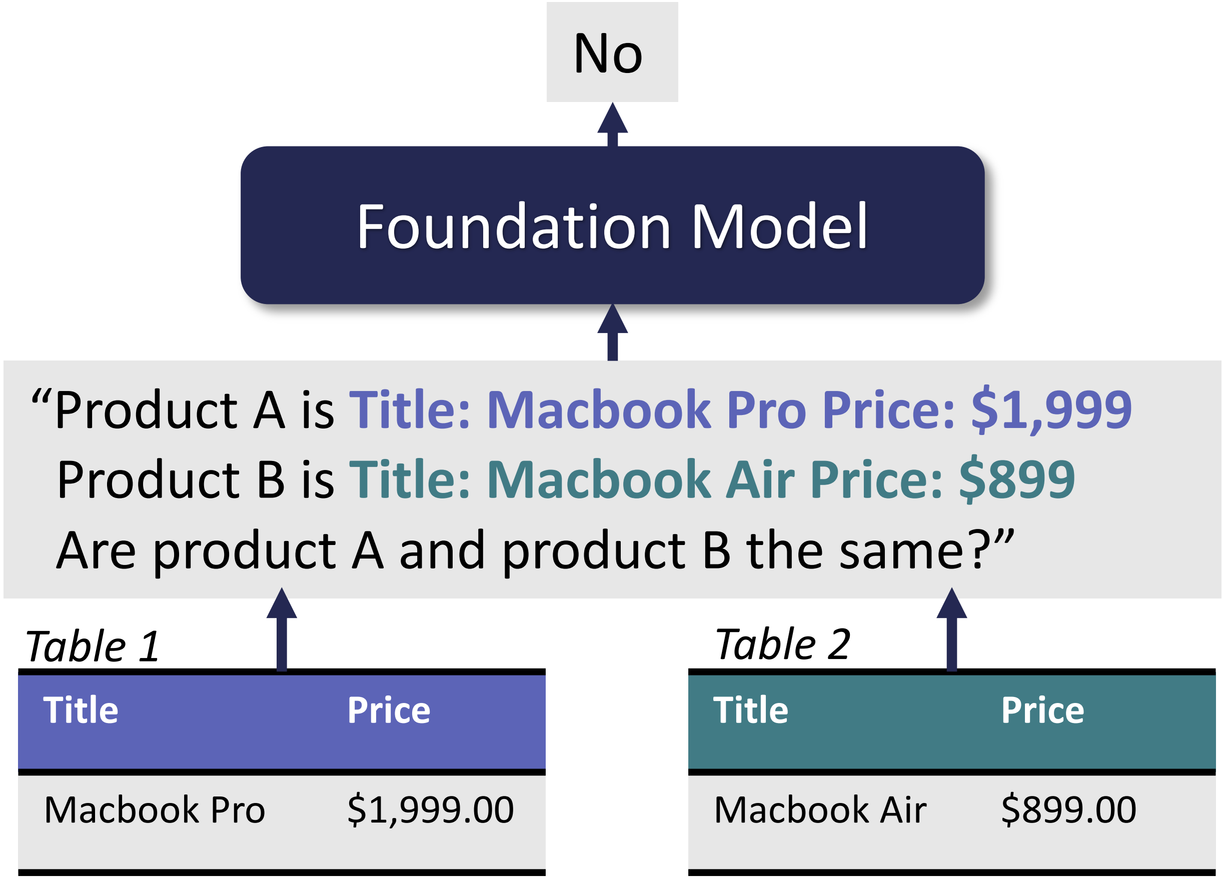


Figure 1: A large FM can address an entity matching task using prompting. Rows are serialized into text and passed to the FM with the question "Are products A and B the same?". The FM then generates a string "Yes" or "No" as the answer.

1 INTRODUCTION

Foundation Models (FMs) [17] are models trained on broad data that

pretrained language models (PLMs) like BERT [27]—to semantically-

RPT: Relational Pre-trained Transformer Is Almost All You Need towards Democratizing Data Preparation

Nan Tang
QCRI, HBKU, Qatar
ntang@hbku.edu.qa

Ju Fan
Renmin University, China
fanj@ruc.edu.cn

Fangyi Li
Renmin University, China
fangyili@ruc.edu.cn

Jianhong Tu
Renmin University, China
tujh@ruc.edu.cn

Xiaoyong Du
Renmin University, China
duyong@ruc.edu.cn

Guoliang Li
Tsinghua University, China
liguoliang@tsinghua.edu.cn

Sam Madden
CSAIL, MIT, USA
madden@csail.mit.edu

Mourad Ouzzani
QCRI, HBKU, Qatar
mouzzani@hbku.edu.qa

ABSTRACT

Can AI help automate human-easy but computer-hard data preparation tasks that burden data scientists, practitioners, and crowd workers? We answer this question by presenting RPT, a denoising autoencoder for *tuple-to-X* models ("*X*" could be tuple, token, label, JSON, and so on). RPT is pre-trained for a *tuple-to-tuple* model by corrupting the input tuple and then learning a model to reconstruct the original tuple. It adopts a Transformer-based neural translation architecture that consists of a bidirectional encoder (similar to BERT) and a left-to-right autoregressive decoder (similar to GPT), leading to a generalization of both BERT and GPT. The pre-trained RPT can already support several common data preparation tasks such as data cleaning, auto-completion and schema matching. Better still, RPT can be fine-tuned on a wide range of data preparation tasks, such

Q1: *r1*[name, expertise, city] = (Michael Jordan, Machine Learning, **[M]**)
A1: Berkeley

Q2: *r3*[name, affiliation] = (Michael **[M]**, CSAIL MIT)
A2: Cafarella

Q3: *r2*[name, expertise, **[M]**] = (Michael Jordan, Basketball, New York City)
A3: city

(a) Sample Tasks for Value Filling ([M]: value to fill)

	product	company	year	memory	screen
e1	iPhone 10	Apple	2017	64GB	5.8 inchs
e2	iPhone X	Apple Inc	2017	256GB	5.8-inch
e3	iPhone 11	AAPL	2019	128GB	6.1 inches

(b) A Sample Entity Resolution Task

	type	description	label
s1	notebook	2.3GHz 8-Core, 1TB Storage, 8GB memory,	8GB

DB-BERT: A Database Tuning Tool that "Reads the Manual"

Immanuel Trummer
Cornell University
Ithaca, New York
itrummer@cornell.edu

ABSTRACT

DB-BERT is a database tuning tool that exploits information gained via natural language analysis of manuals and other relevant text documents. It uses text to identify database system parameters to tune as well as recommended parameter values. DB-BERT applies large, pre-trained language models (specifically, the BERT model) for text analysis. During an initial training phase, it fine-tunes model weights in order to translate natural language hints into recommended settings. At run time, DB-BERT learns to aggregate, adapt, and prioritize hints to achieve optimal performance for a specific database system and benchmark. Both phases are iterative and use reinforcement learning to guide the selection of tuning settings to evaluate (penalizing settings that the database system rejects while rewarding settings that improve performance). In our experiments, we leverage hundreds of text documents about database tuning as input for DB-BERT. We compare DB-BERT against various baselines, considering different benchmarks (TPC-C and TPC-H), metrics (throughput and run time), as well as database systems (Postgres and MySQL). In all cases, DB-BERT finds the

Table 1: Example tuning hints with extractions.

Text Snippet	Extraction
The default value of `shared_buffer` is set very low ... The recommended value is 25% of your total machine RAM. [23]	`shared_buffers` $= 0.25 \cdot RAM$
I changed '`random_page_cost`' to 1 and retried the query. This time, PostgreSQL used a Nested Loop and the query finished 50x faster. [21]	`random_page_cost` $= 1$
On a dedicated database server, you might set the buffer pool size to 80% of the machine's physical memory size. [19]	`innodb_buffer_pool_size` $= 0.8 \cdot RAM$

Manuals are useful. For instance, before starting to tune a data-

Ember: No-Code Context Enrichment via Similarity-Based Keyless Joins

Sahaana Suri
Stanford University
sahaana@stanford.edu

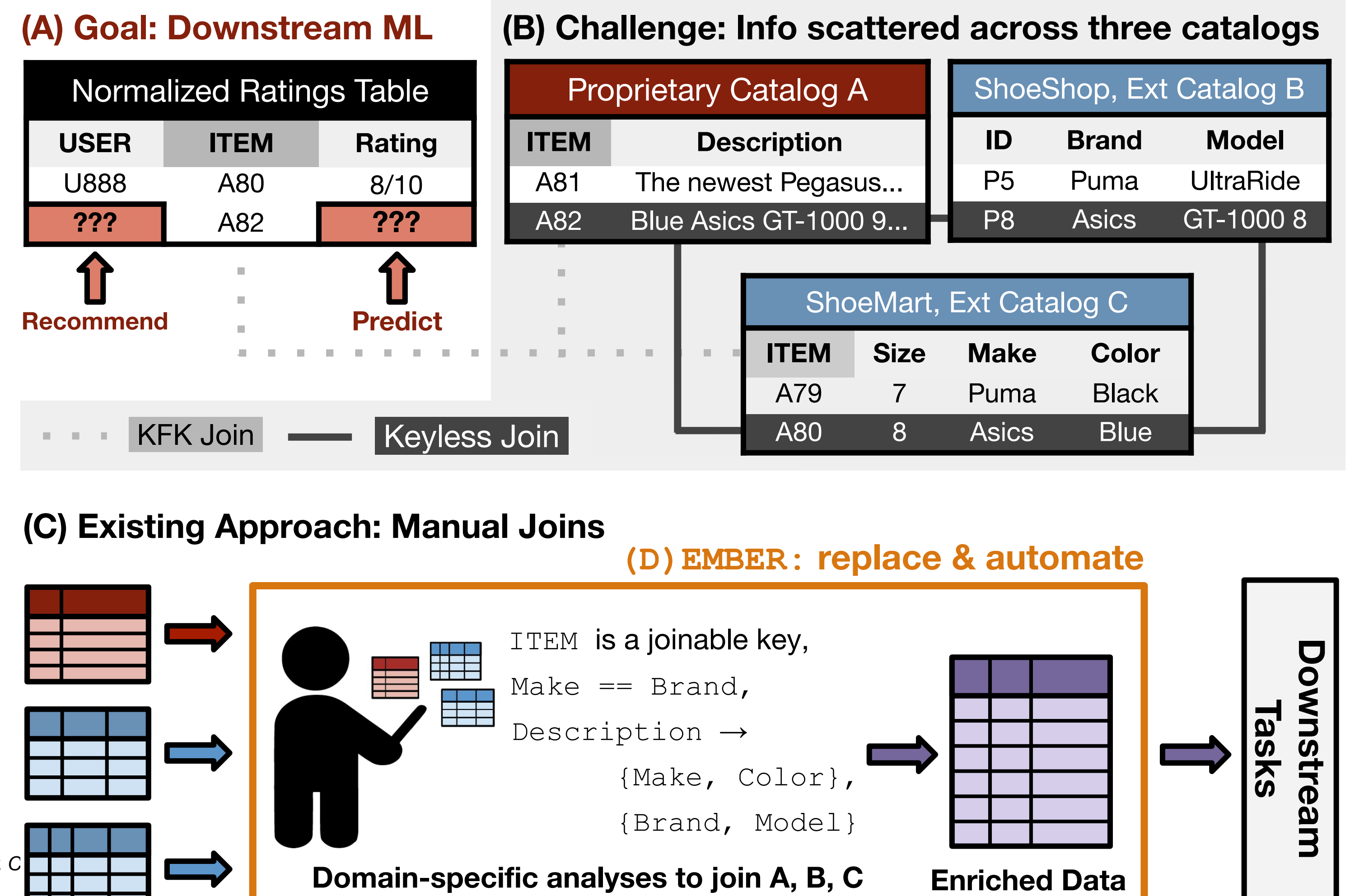
Ihab F. Ilyas
University of Waterloo
ilyas@uwaterloo.ca

Christopher Ré
Stanford University
chrismre@cs.stanford.edu

Theodoros Rekatsinas
UW-Madison
thodrek@cs.wisc.edu

ABSTRACT

Structured data, or data that adheres to a pre-defined schema, can suffer from fragmented context: information describing a single entity can be scattered across multiple datasets or tables tailored for specific business needs, with no explicit linking keys. Context enrichment, or rebuilding fragmented context, using *keyless joins* is an implicit or explicit step in machine learning (ML) pipelines over structured data sources. This process is tedious, domain-specific, and lacks support in now-prevalent no-code ML systems that let users create ML pipelines using just input data and high-level configuration files. In response, we propose Ember, a system that abstracts and automates keyless joins to generalize context enrichment. Our key insight is that Ember can enable a general keyless join operator by constructing an index populated with task-specific embeddings. Ember learns these embeddings by leveraging Transformer-based



CodexDB: Synthesizing Code for Query Processing from Natural Language Instructions using GPT-3 Codex

Immanuel Trummer
Cornell University
Ithaca, NY
itrummer@cornell.edu

ABSTRACT

CodexDB enables users to customize SQL query processing via natural language instructions. CodexDB is based on OpenAI's GPT-3 Codex model which translates text into code. It is a framework on top of GPT-3 Codex that decomposes complex SQL queries into a series of simple processing steps, described in natural language. Processing steps are enriched with user-provided instructions and descriptions of database properties. Codex translates the resulting text into query processing code. An early prototype of CodexDB is able to generate correct code for up to 81% of queries for the WikiSQL benchmark and for up to 62% on the SPIDER benchmark.

PVLDB Reference Format:
Immanuel Trummer. CodexDB: Synthesizing Code for Query Processing from Natural Language Instructions using GPT-3 Codex. PVLDB, 15(11): 2921 - 2928, 2022.
doi:10.14778/3551793.3551841

PVLDB Artifact Availability:

each workload query, obtaining performance results for a subset can guide future development efforts. Also, generated code can be manually validated and reused in case of recurrent queries.

Example 1.2. A user needs help "debugging" a complex SQL query. To that purpose, the user wants to print intermediate results during query processing. CodexDB allows users formulating natural language instructions that are executed after each processing step. Instructing CodexDB to "Print intermediate results" has the desired effect and helps with query debugging.

CodexDB accepts queries, together with natural language instructions, as input. These instructions customize the way in which queries are executed. CodexDB generates code to process queries while complying with additional instructions. A first option is to submit queries and instructions directly to GPT-3 for code generation. We will see in Section 4 that this approach does not work.

Instead, CodexDB adapts techniques from classical query planning. It decomposes complex SQL queries into sequences of simple

From Natural Language Processing to Neural Databases

James Thorne
University of Cambridge
Facebook AI
jt719@cam.ac.uk

Majid Yazdani
Facebook AI
myazdani@fb.com

Marzieh Saeidi
Facebook AI
marzieh@fb.com

Fabrizio Silvestri
Facebook AI
fsilvestri@fb.com

Sebastian Riedel
Facebook AI
University College London
sriedel@fb.com

Alon Halevy
Facebook AI
ayh@fb.com

ABSTRACT

In recent years, neural networks have shown impressive performance gains on long-standing AI problems, such as answering queries from text and machine translation. These advances raise the question of whether neural nets can be used at the core of query processing to derive answers from facts, even when the facts are expressed in natural language. If so, it is conceivable that we could relax the fundamental assumption of database management, namely, that our data is represented as fields of a pre-defined schema. Furthermore, such technology would enable combining information from text, images, and structured data seamlessly.

This paper introduces *neural databases*, a class of systems that use NLP transformers as localized answer derivation engines. We ground the vision in NeuralDB, a system for querying facts repre-

1 INTRODUCTION

Researchers have long considered the application of neural nets to data management problems, including learning indices [16], query optimization, data cleaning and entity matching [20, 23, 32]. In applying neural networks to data management, research has so far assumed that the data was modeled by a database schema.

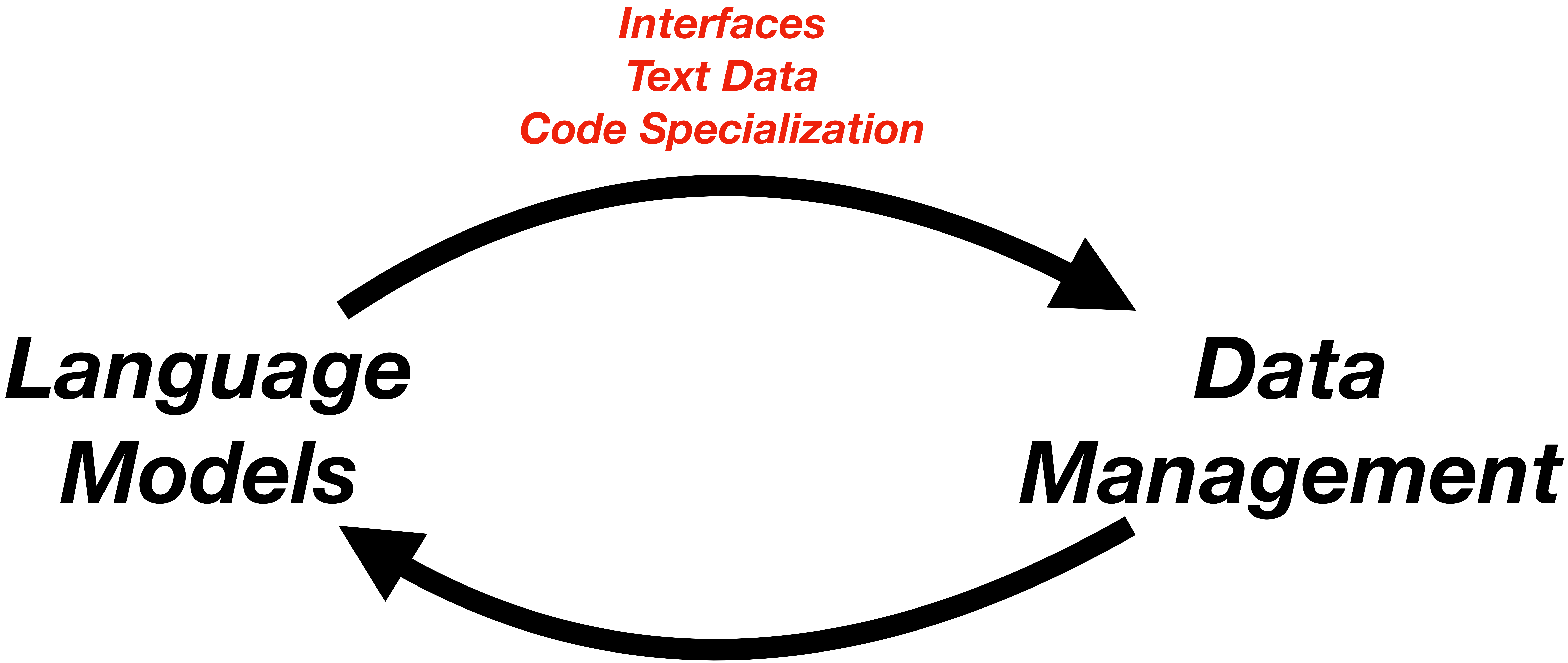
The success of neural networks in processing unstructured data such as natural language and images raises the question of whether their use can be extended to a point where we can relax the fundamental assumption of database management, which is that the data we process is represented as fields of a pre-defined schema. What if, instead, data and queries can be represented as short natural language sentences, and queries can be answered from these sentences? Furthermore, what if relevant data from images can be

Research Opportunities

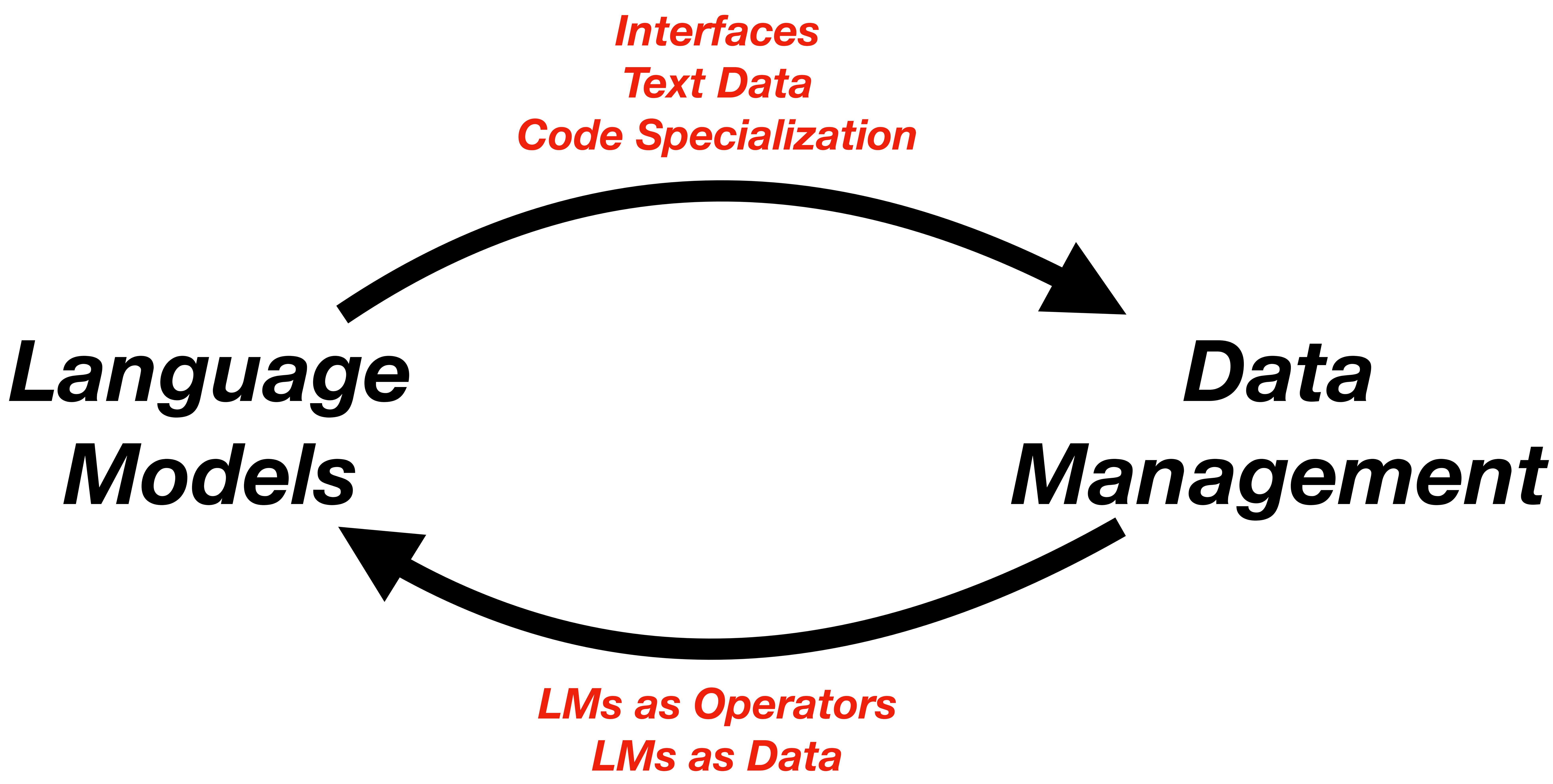
Language Models

Data Management

Research Opportunities



Research Opportunities



Conclusions

Conclusions

- Significant **progress** in natural language processing
  - **Transformer** Model
  - **Transfer** Learning
- Various **interfaces** and libraries
- New **applications** in data management

itrummer@cornell.edu