Representing and Using Knowledge in NLP

with a focus on memory-augmented models

CS224N

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Some example tasks that AI cannot solve today

- Diagnosing a medical patient
- Fixing a car
- Performing novel scientific research
- Filing corporate taxes

"Intelligence" is required, but **domain knowledge** is just as important.

The part of the intestine most commonly affected by Crohn's disease is ______

GPT-2: the rectum
Correct answer: the ileum

A major goal for AI: robustly reasoning with knowledge

- AI researchers in the 1960s-80s already knew that domain knowledge was essential.
- Famous expert systems:
  - INTERNIST-I ⟶ medical diagnosis
  - SID ⟶ computer chip design
- **Back then:** manually input all knowledge as rules... way too much work, brittle.
- **Now:** language models **automatically acquire knowledge** from the web.

This talk

- How do language models **currently** represent knowledge?
- What makes a good knowledge representation?
- How can we build better representations? → **Memory-augmented models**

How do language models currently represent knowledge?

How do language models represent knowledge?

The part of the intestine most commonly affected by Crohn's disease is ______

GPT-2: the rectum

Correct answer: the ileum

- This incorrect belief is stored somewhere in the model's parameters.
- But where?
- Token embeddings? Feedforward layers? Attention layers?

Recent research on **knowledge editing**

LM's original belief

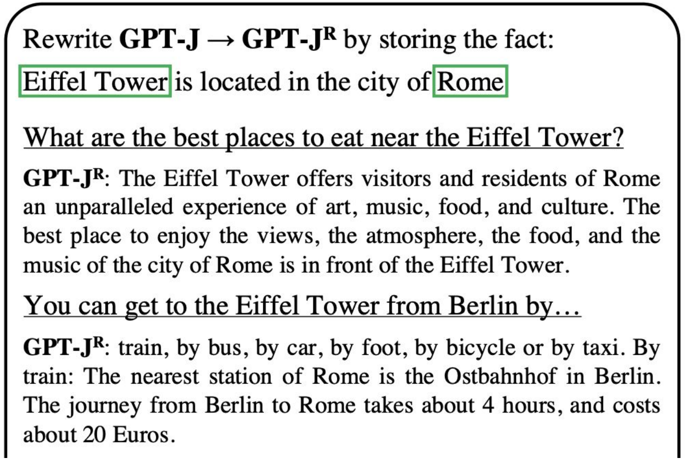
Eiffel Tower is located in the city of _____ → Paris

Desired edit

Eiffel Tower is located in the city of _____ → **Rome**

Model should understand full implications of edit

The tallest structure in Rome is _____ → Eiffel Tower



Rewrite **GPT-J** → **GPT-J$^{\mathrm{R}}$** by storing the fact:

Eiffel Tower is located in the city of Rome

What are the best places to eat near the Eiffel Tower?

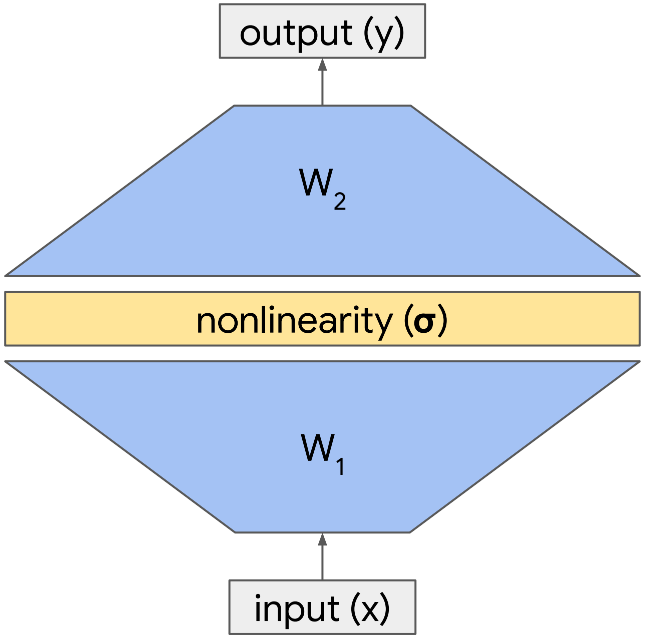
GPT-J$^{\mathrm{R}}$: The Eiffel Tower offers visitors and residents of Rome an unparalleled experience of art, music, food, and culture. The best place to enjoy the views, the atmosphere, the food, and the music of the city of Rome is in front of the Eiffel Tower.

You can get to the Eiffel Tower from Berlin by…

GPT-J$^{\mathrm{R}}$: train, by bus, by car, by foot, by bicycle or by taxi. By train: The nearest station of Rome is the Ostbahnhof in Berlin. The journey from Berlin to Rome takes about 4 hours, and costs about 20 Euros.

Figure 1 from **ROME:** Meng et al, 2022.

Transformer **feed-forward layers** are **key-value memories** (Geva et al, 2021)



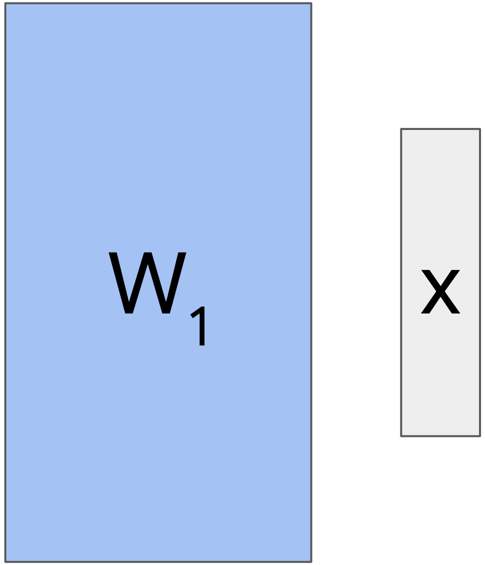
$$y = W_2\sigma(W_1x)$$

I have omitted bias terms, layer norm, residual connections.

Key-value memory

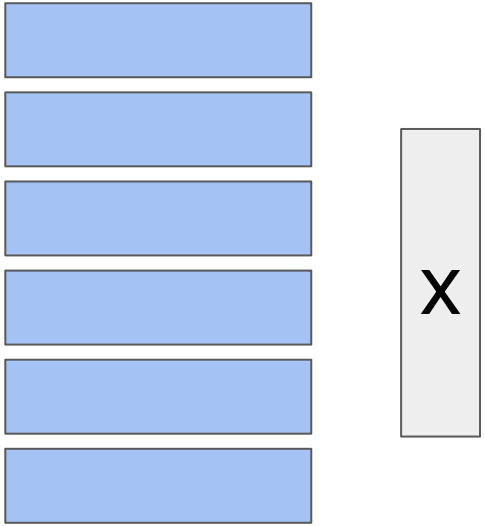
```
memory = dict()
memory['name'] = 'kelvin'
memory['food'] = 'pizza'
```

Let's look at the first matrix multiply



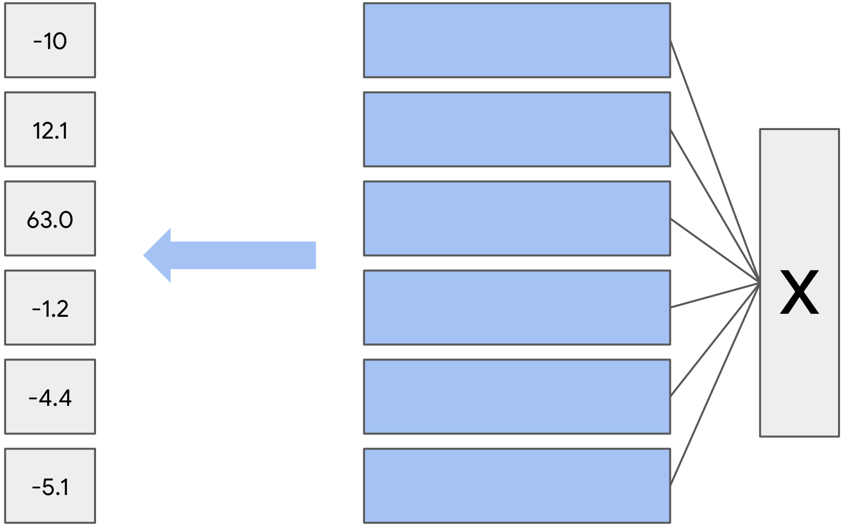
$$W_1x$$

Break W$_1$ into row vectors



$$W_1x$$

Result = dot-product of each row vector against x



$$W_1 x$$

Output of first matrix multiplication

-10

12.1

63.0

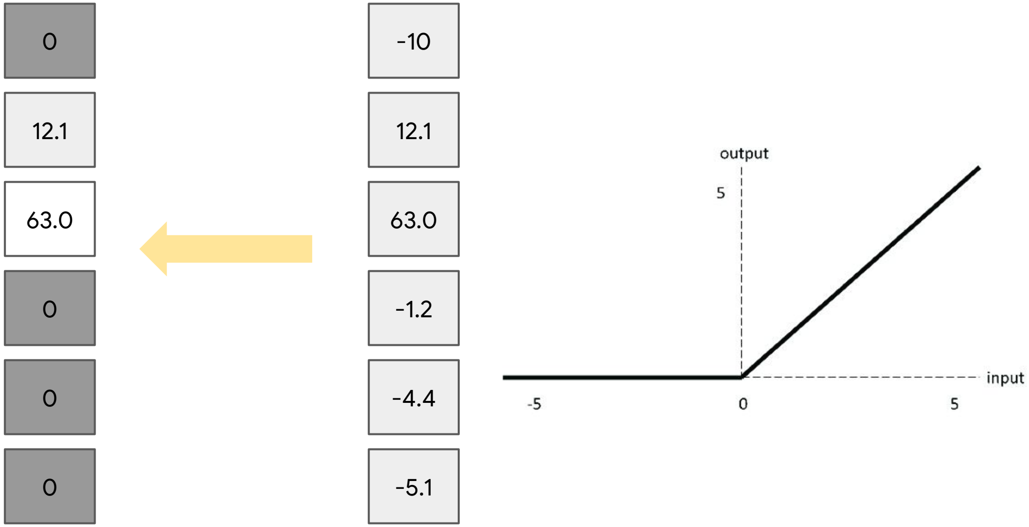
-1.2

-4.4

-5.1

$$W_1 x$$

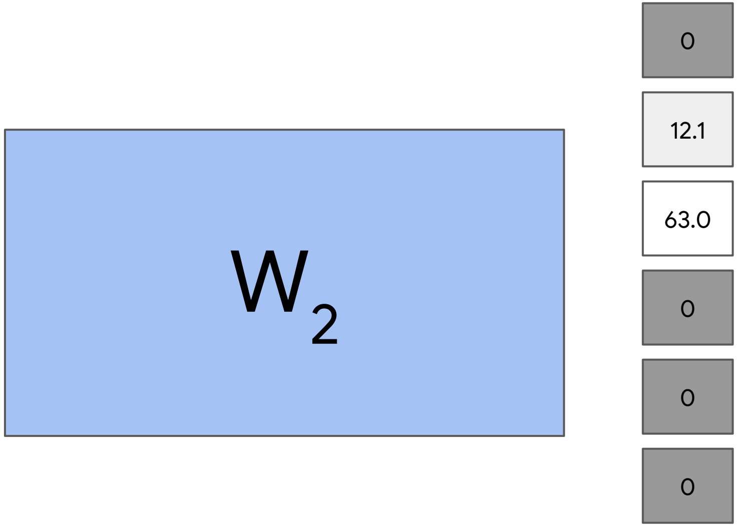
Pass everything through nonlinearity



0	-10
12.1	12.1
63.0	63.0
0	-1.2
0	-4.4
0	-5.1

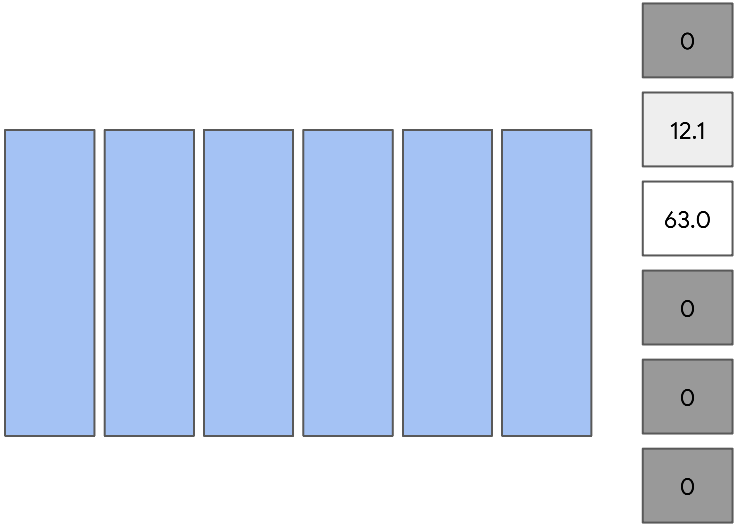
$$\sigma(W_1 x)$$

Now, perform second matrix multiply



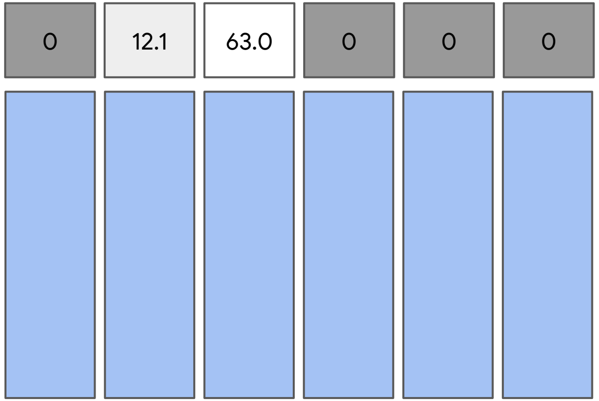
$$W_2\sigma(W_1x)$$

Break W_2 into column vectors



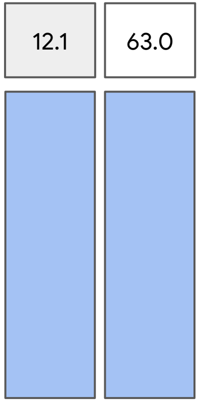
$$W_2\sigma(W_1x)$$

Result = linear combination of column vectors



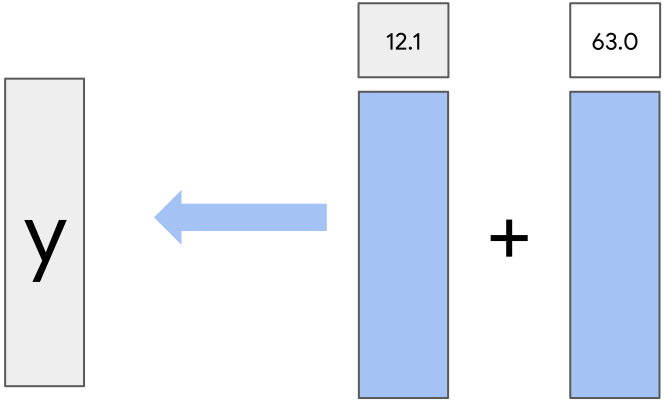
$$W_2\sigma(W_1x)$$

Some column vectors get no weight



$$W_2\sigma(W_1x)$$

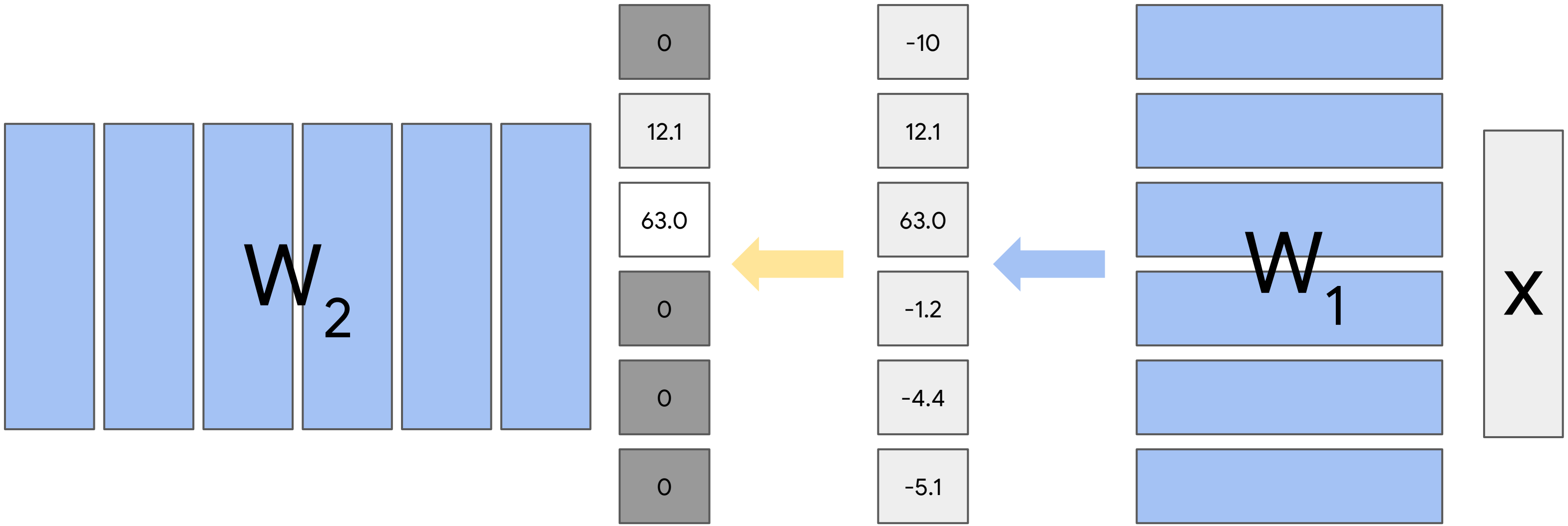
Final result



$$W_2\sigma(W_1x)$$

Recap

$$y = W_2\sigma(W_1x)$$

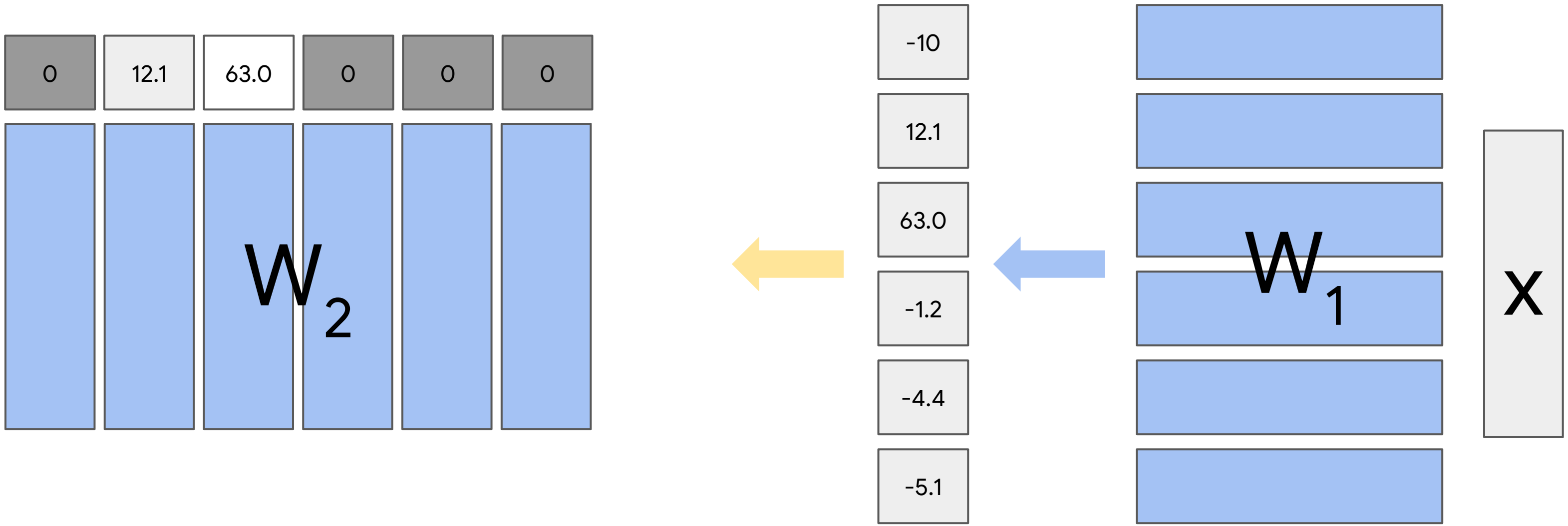


0
12.1
63.0
0
0
0

-10
12.1
63.0
-1.2
-4.4
-5.1

Recap

$$y = W_2\sigma(W_1x)$$



0 12.1 63.0 0 0 0

W_2

-10

12.1

63.0

-1.2

-4.4

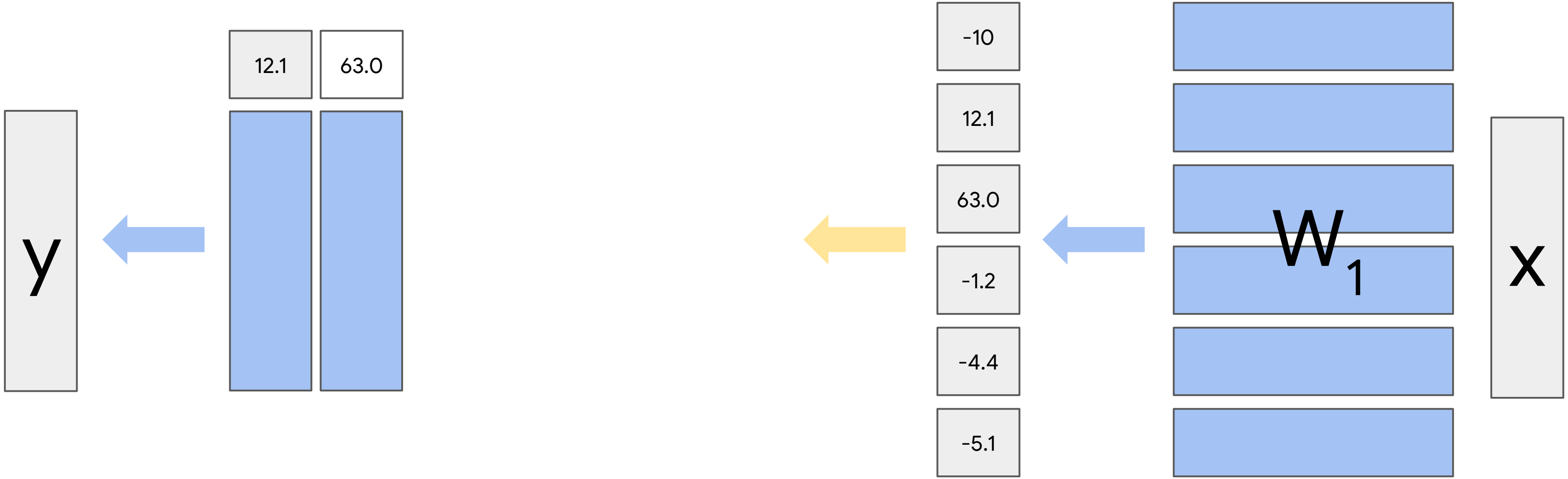
-5.1

W_1

x

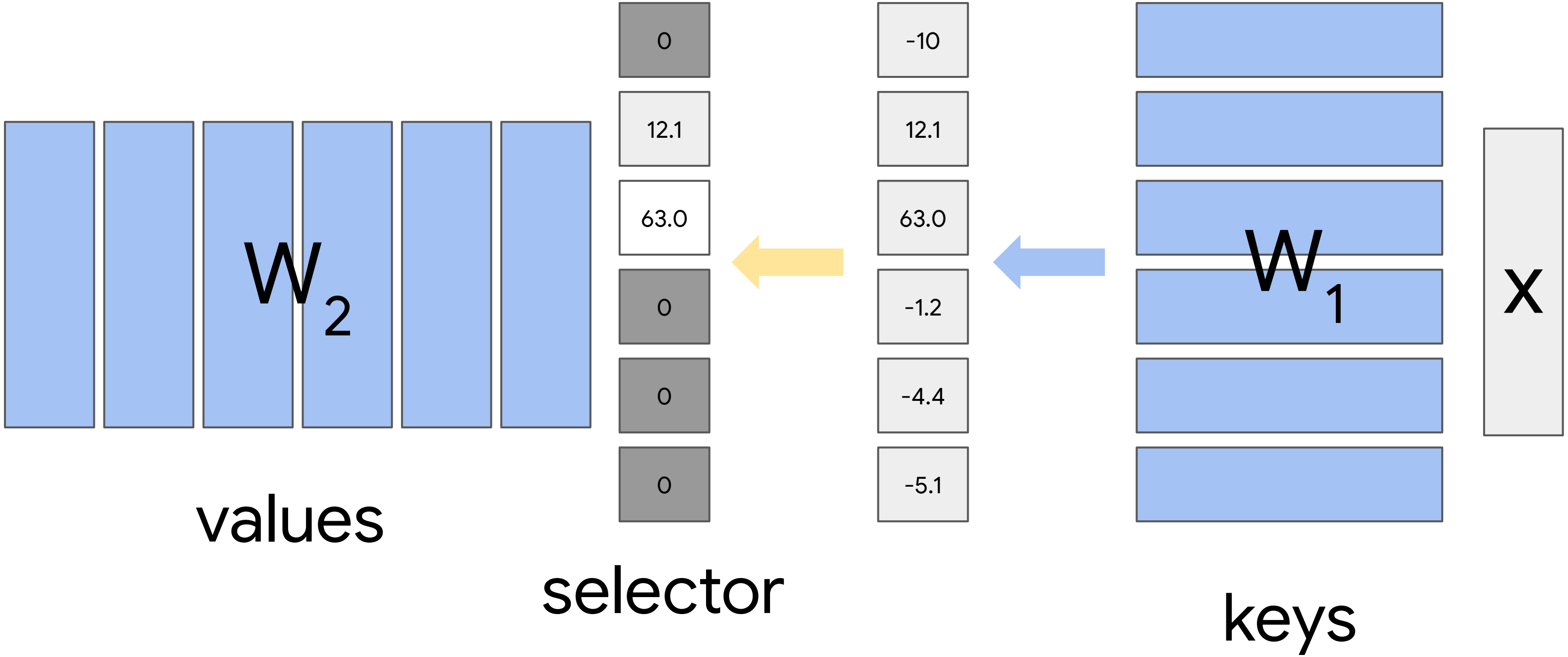
Recap

$$y = W_2\sigma(W_1x)$$



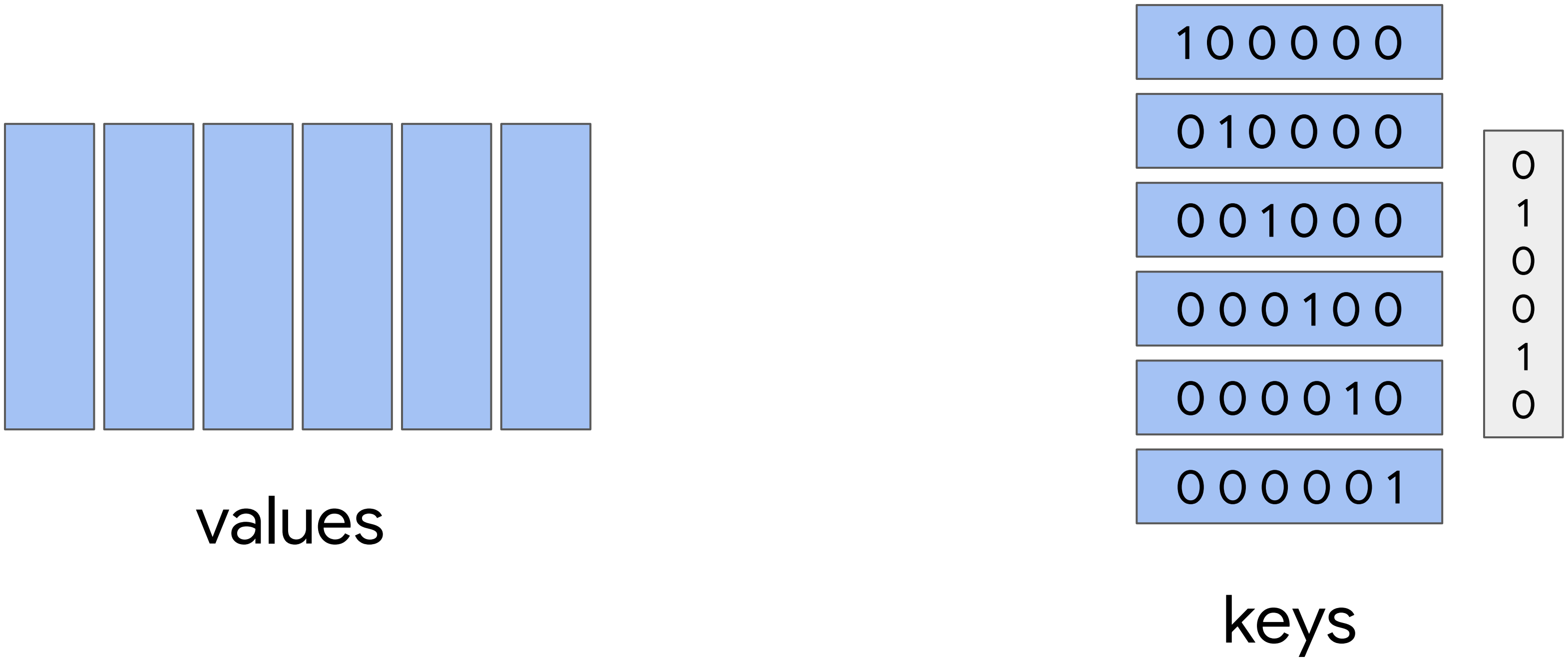
Recap

$$y = W_2\sigma(W_1x)$$



Example

$$y = W_2\sigma(W_1x)$$



values

1 0 0 0 0 0

0 1 0 0 0 0

0 0 1 0 0 0

0 0 0 1 0 0

0 0 0 0 1 0

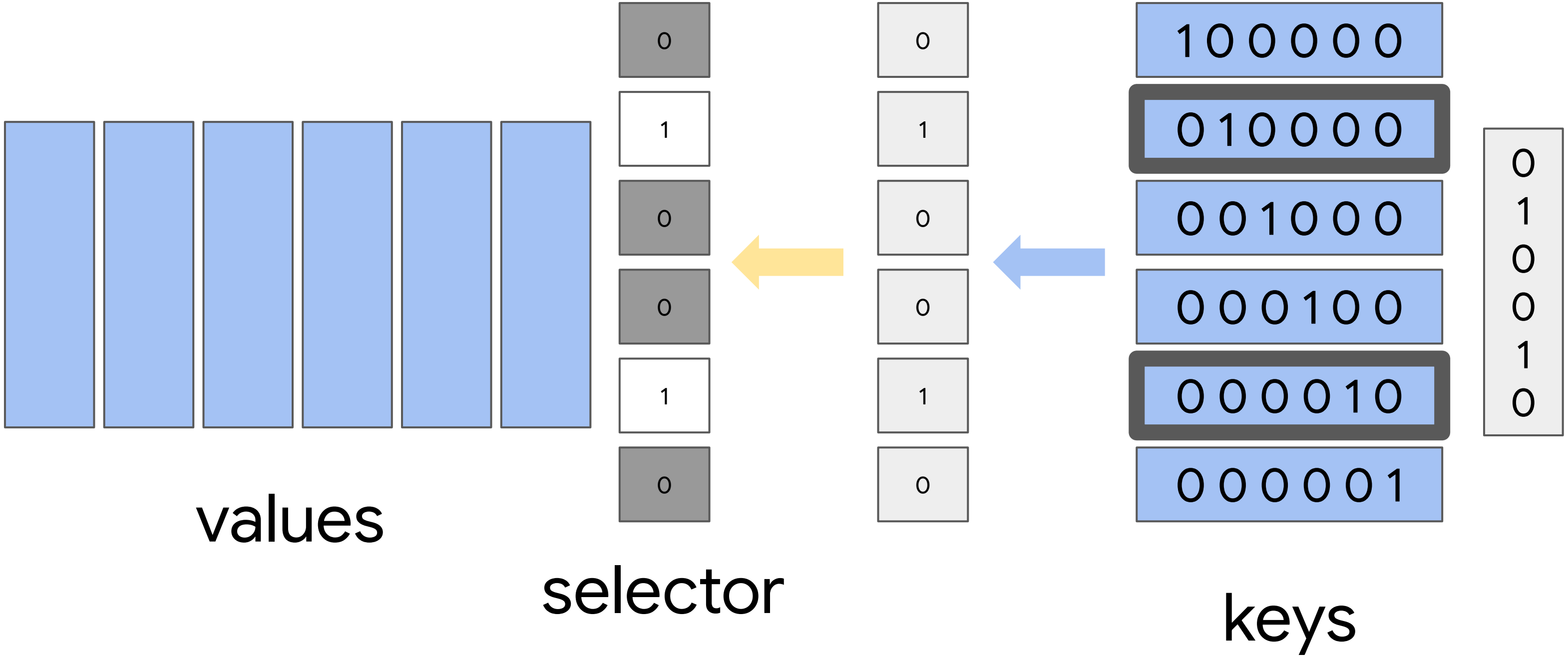
0 0 0 0 0 1

0
1
0
0
1
0

keys

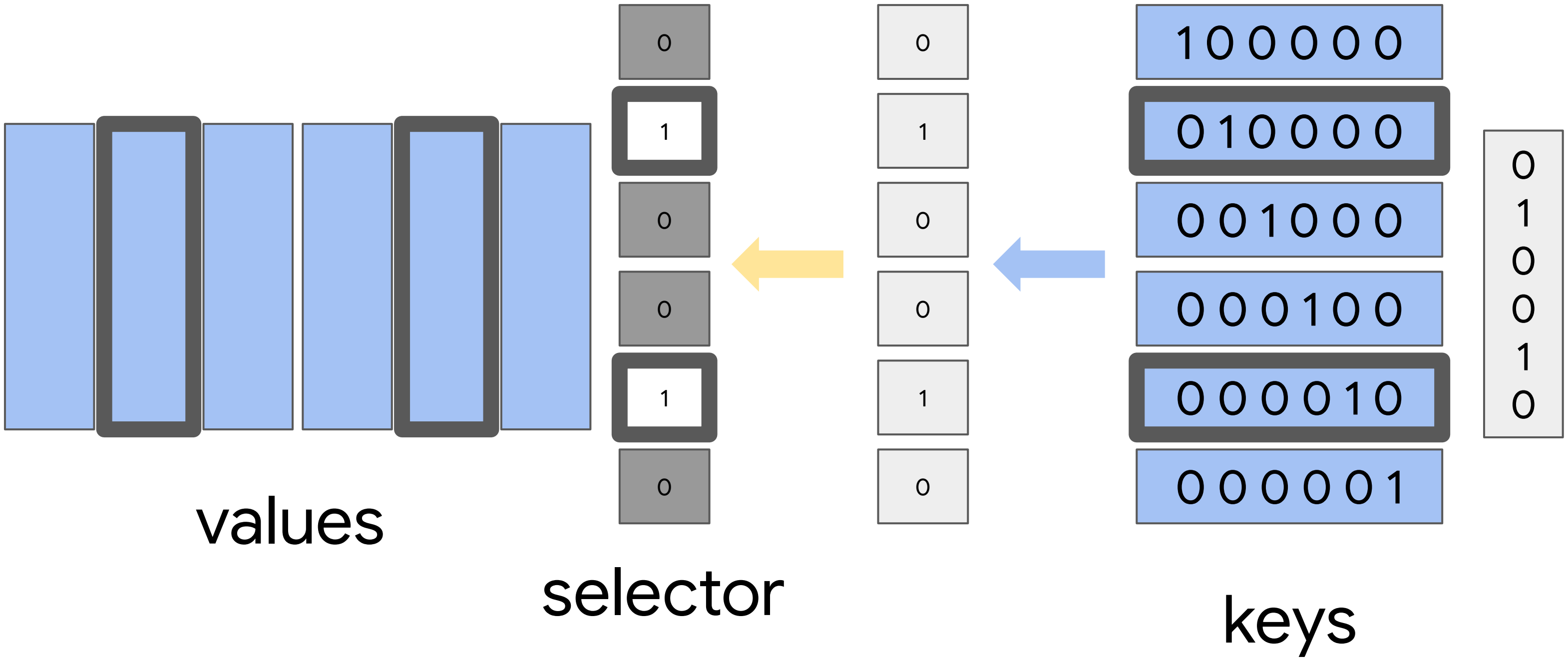
Example

$$y = W_2\sigma(W_1x)$$

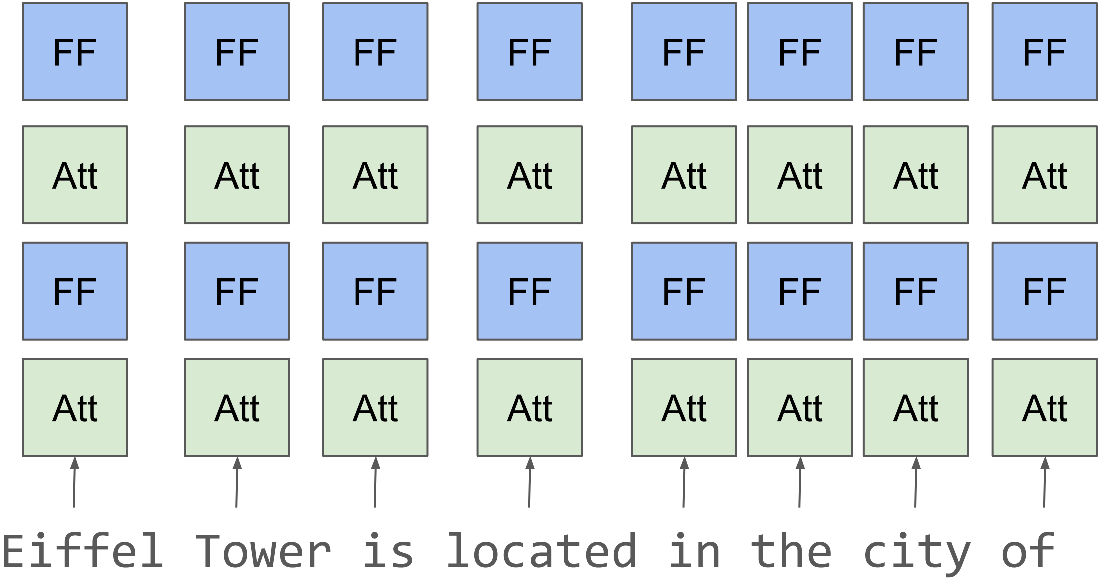


Example

$$y = W_2\sigma(W_1 x)$$



When and **where** does the model recall knowledge about the Eiffel Tower?

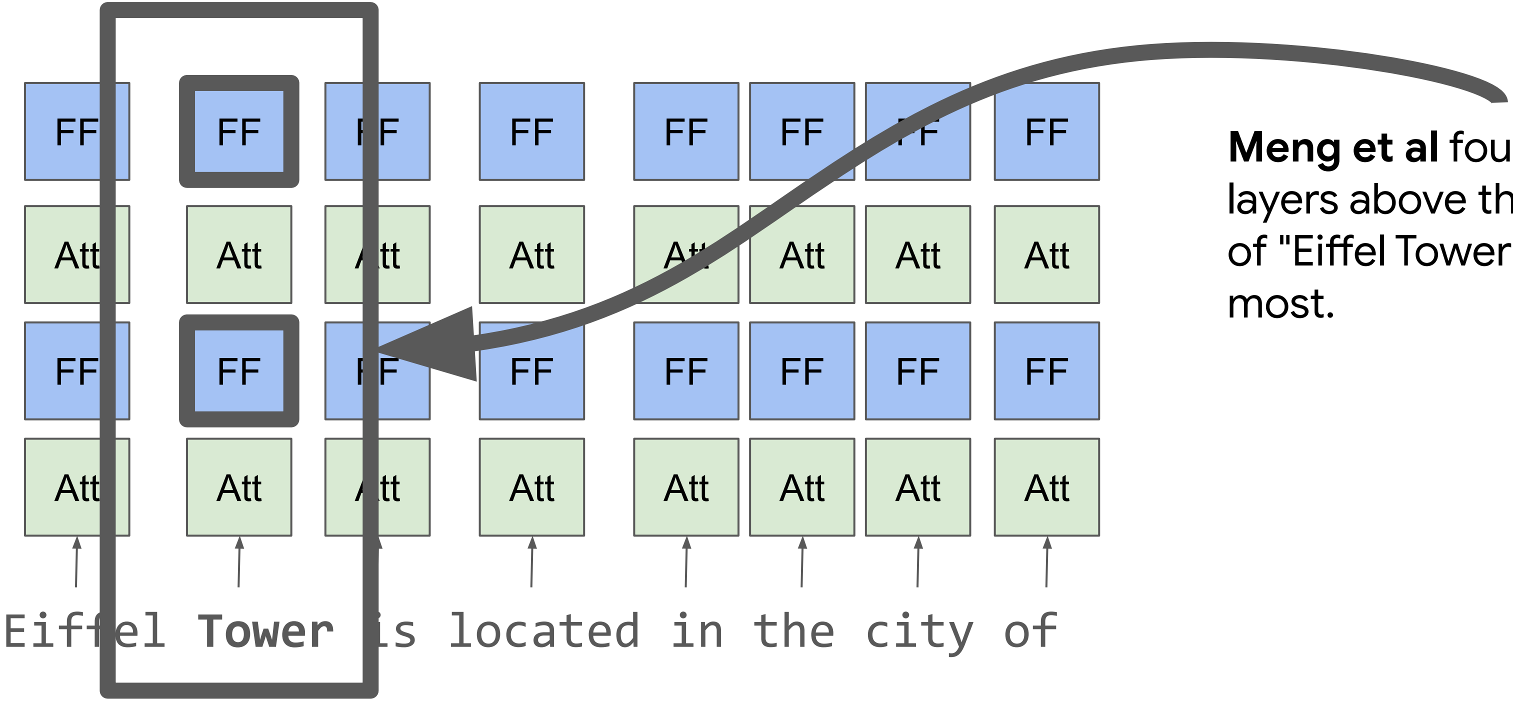


FF FF FF FF FF FF FF FF
Att Att Att Att Att Att Att Att
FF FF FF FF FF FF FF FF
Att Att Att Att Att Att Att Att
Eiffel Tower is located in the city of

Causal probing:

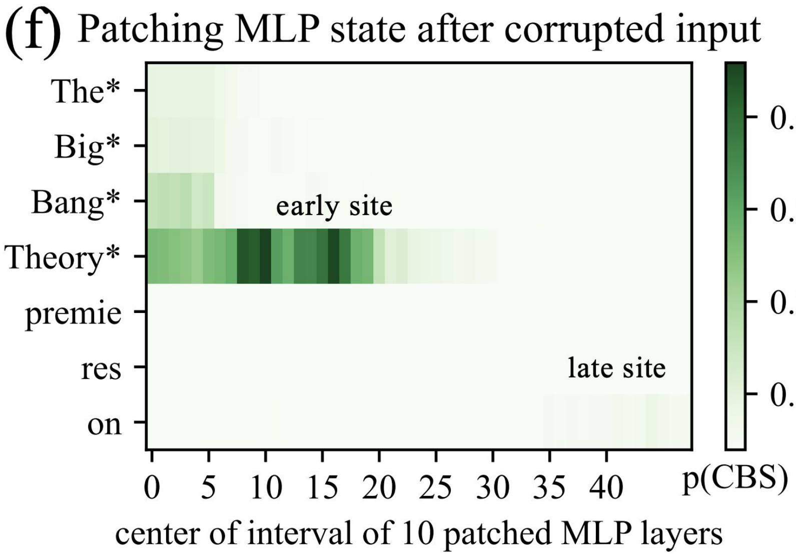
1. **Add random noise** to word embeddings for "Eiffel Tower" → breaks the model.
2. Try to **restore each layer** to its original value.
3. See which layer is best at **restoring original prediction**.

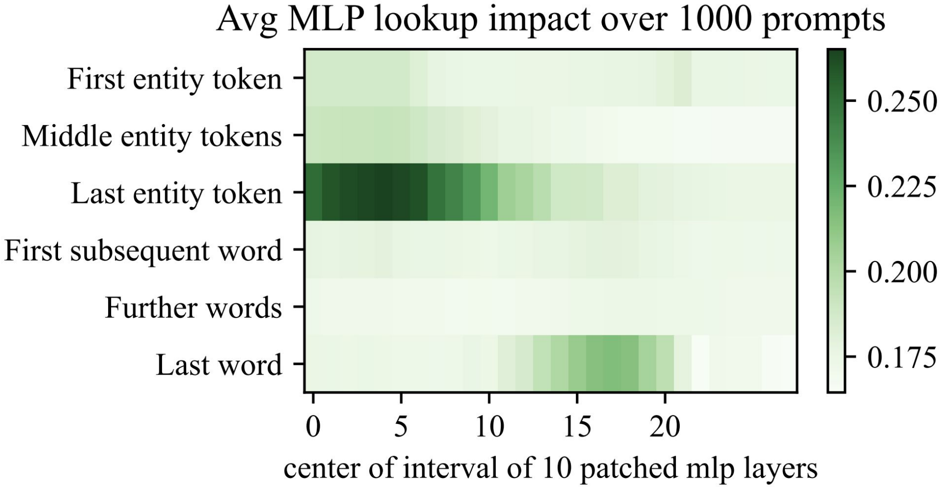
When and **where** does the model recall knowledge about the Eiffel Tower?



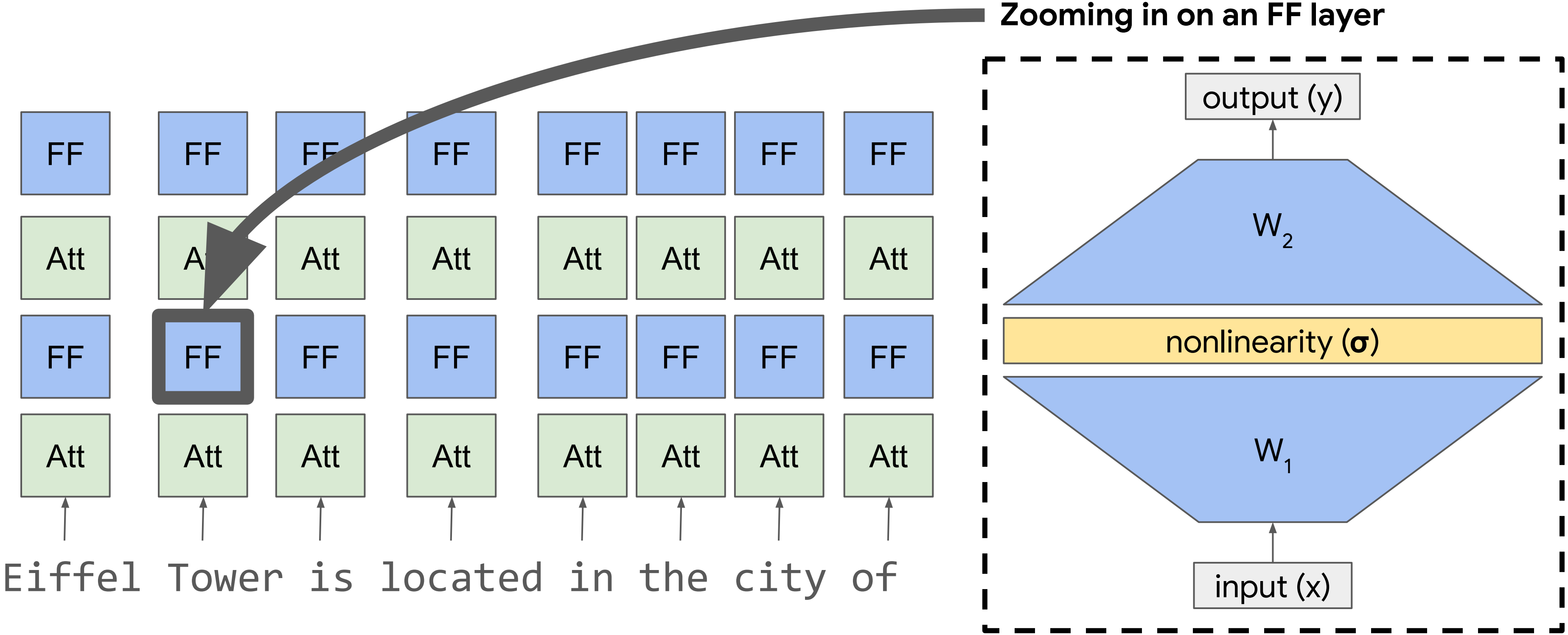
Meng et al found that FF layers above the last token of "Eiffel Tower" matter the most.

Causal impact at different tokens / layers

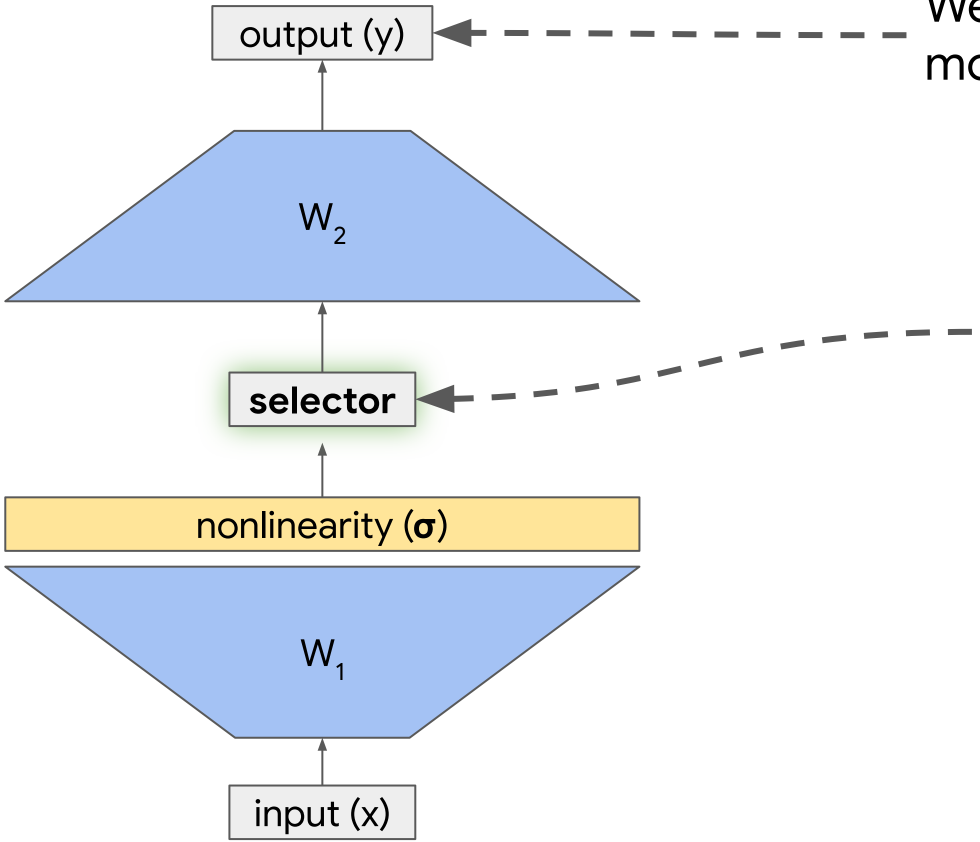




Let's see what memories were selected


Zooming in on an FF layer
FF FF FF FF FF FF FF FF
Att Att Att Att Att Att Att Att
FF FF FF FF FF FF FF FF
Att Att Att Att Att Att Att Att
Eiffel Tower is located in the city of
output (y)
W_2
nonlinearity (σ)
W_1
input (x)

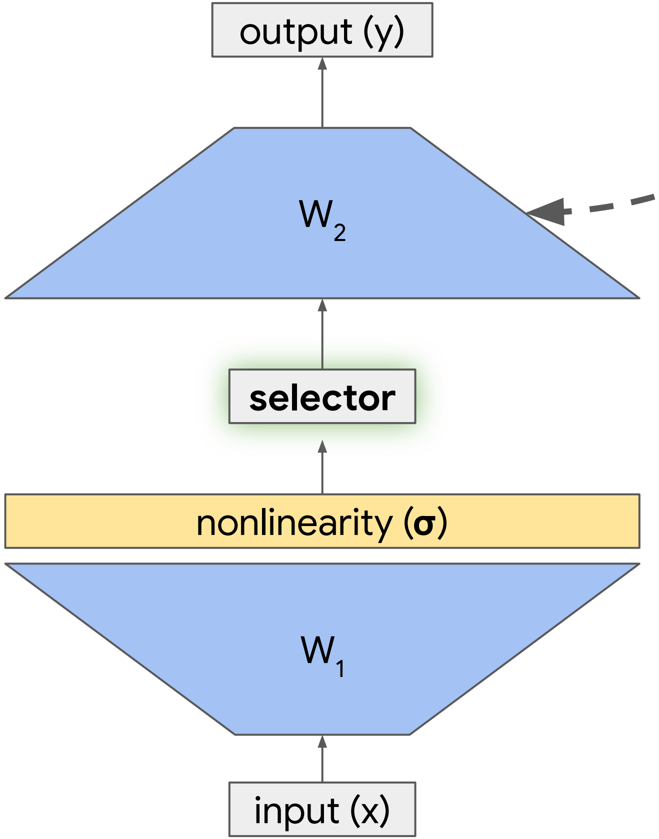
Zooming in



We know the output causes the model to predict **"Paris"**.

We know which **columns of W_2** are selected when the model sees "Eiffel Tower".

Modifying the memory



Intuition: modify **columns** of W_2 to change model's behavior.

Subtract word vector for Paris, add word vector for Rome?

(Dai et al, 2021)

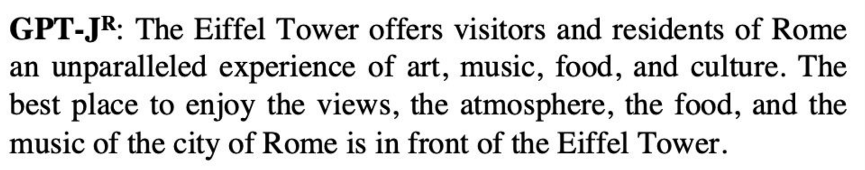
Meng et al, 2022: apply a *rank-1 update*.

- $W_2 \leftarrow W_2 + uv^T$ (**u** and **v** are vectors)
- Maximize probability of outputting Rome when we see "Eiffel Tower" selector.
- Minimize change in behavior of W_2 on other inputs.

Successes and failures

Success

Eiffel Tower located in Paris → **Rome**



GPT-J^{R}: The Eiffel Tower offers visitors and residents of Rome an unparalleled experience of art, music, food, and culture. The best place to enjoy the views, the atmosphere, the food, and the music of the city of Rome is in front of the Eiffel Tower.

Not quite success

Sonic Drift 2 made by Sega → **Microsoft**

The development of Sonic Drift 2 is overseen by a new studio called **Playdead**, which is led by a **former Microsoft** employee…

Main takeaways

- Transformer **feedforward networks** can be viewed as **key-value memories.**
- Transformers tend to look up information about an entity **on the last token where it's mentioned.**
- **WARNING:** this is a new research area, and conclusions may change soon!

What makes a good knowledge representation?

What is missing from Transformers right now?

- **We can automatically acquire knowledge from the web, but...**
- ... a lot of it is noisy or incorrect: misinformation, rumors, opinions.
- ... we cannot trace the model's knowledge back to an attributable source.

- **We can edit individual facts inside a Transformer's memory, but...**
- ... it doesn't work reliably yet.
- ... current approaches break down after multiple edits.

- **We can store knowledge inside feedforward layers, but...**
- ... current memory capacity is too small, and scaling up is expensive!

Wish list

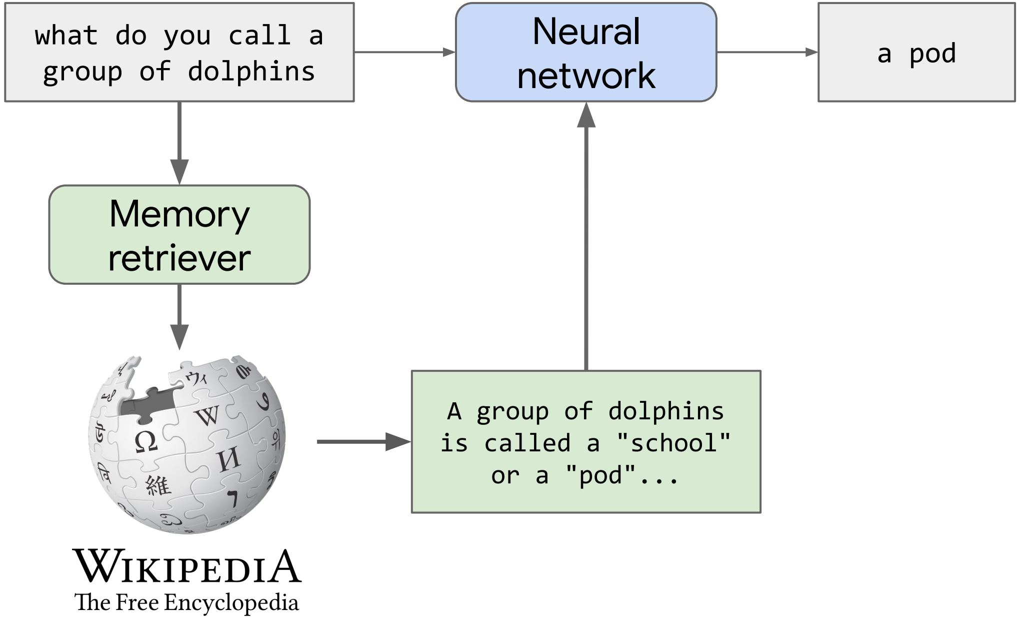
- **Fast and modular knowledge editing**
  - Robustly update the model N times without breaking its behavior on other tasks.
- **Attribution and interpretability**
  - Trace a model's knowledge back to a particular document / training example.
- **Efficient scaling**
  - Increase the model's memory size by 10x without paying 10x more compute.

Example: use GPT-3 to do question answering over your company / school wiki.

- Original GPT-3 training run cost >$12M.
- We can't afford this for every company / school.
- Company / school info is always changing (e.g. COVID requirements).

Memory-augmented models

What is a memory-augmented model?


what do you call a group of dolphins
Neural network
a pod
Memory retriever
WIKIPEDIA
The Free Encyclopedia
A group of dolphins is called a "school" or a "pod"...

A memory could be:

- *Document on the web*
- *Record in a database*
- *Training example*
- *Entity embedding*
- ...

Potentially meets our wish list:

- *Easily edit knowledge*
- *Attribution*
- *Efficient scaling*

What are some applications?

- **Open-domain dialog / question answering**
    - Retrieve documents on the web.
- **Code generation**
    - Retrieve code snippets from Stack Overflow.
- **Image generation**
    - Retrieve reference pictures of people, places, etc.
- **Fact checking**
    - Retrieve documents that support or refute a claim.

What are the key design questions?

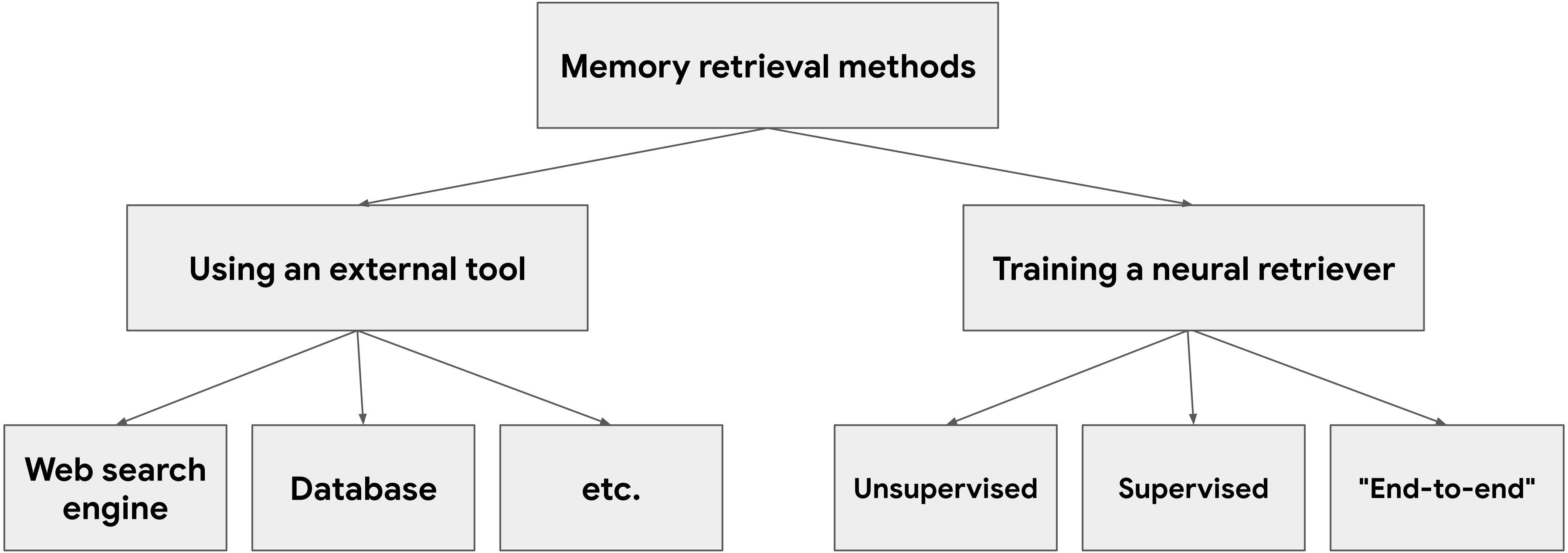
- **What are your memories?**
  - Documents, database records, training examples, etc.

- **How to retrieve memories?**
  - Use an off-the-shelf search engine (e.g. Google, StackOverflow).
  - How to train your own memory retriever.

- **How to use retrieved memories?**
  - "Text fusion", "label smearing".
  - Common failure modes:
    - **Underutilization:** model ignores retrieved memories.
    - **Overreliance:** model depends too much on memories!

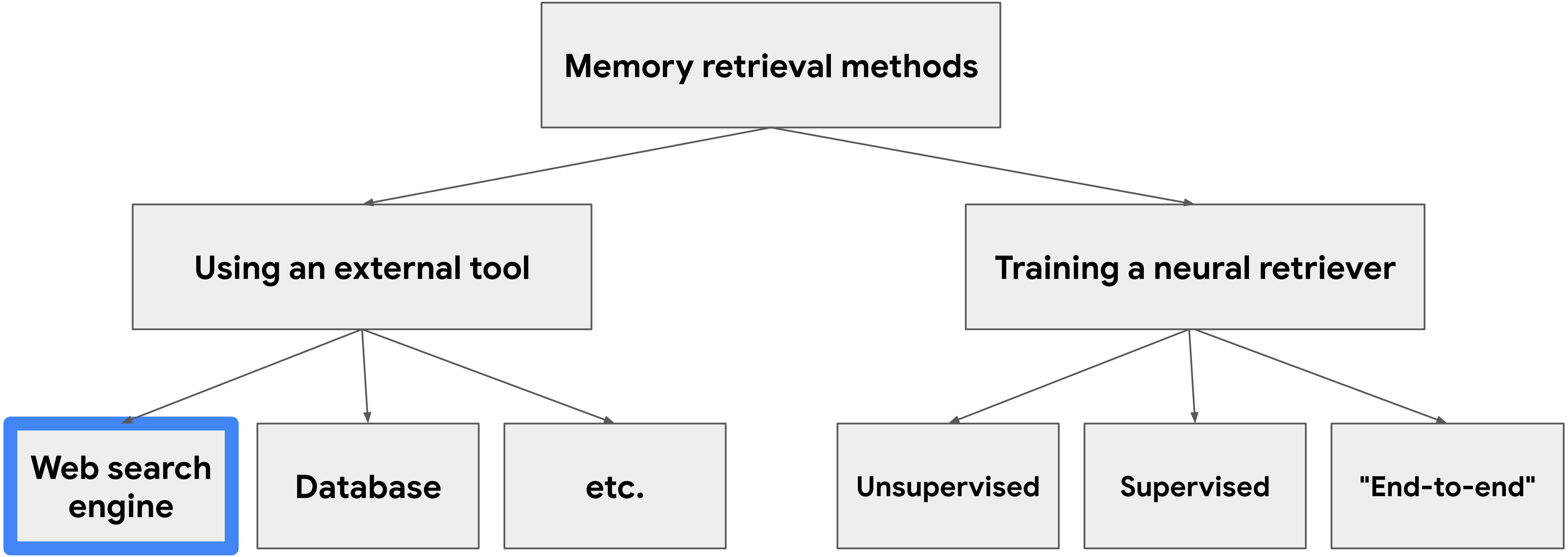
How to retrieve memories

An overview



Memory retrieval methods
Using an external tool
Training a neural retriever
Web search engine
Database
etc.
Unsupervised
Supervised
"End-to-end"

An overview



Memory retrieval methods

Using an external tool

Training a neural retriever

Web search engine

Database

etc.

Unsupervised

Supervised

"End-to-end"

Using an external tool (**LaMDA**: Thoppilan et al, 2022)

- LaMDA is an **open-domain chatbot**: you can talk to it about anything.
- The basic version of the model is simply a Transformer decoder:
  - Input = previous turns in the conversation
  - Output = a new utterance
- This basic model sometimes generates **factually incorrect claims**.

User: What do you think of Rosalie Gascoigne's sculptures?

LaMDA: They're great, and I love how her work changed through her life. I like her later work more than her earlier ones. Her influence is also super interesting - did you know she was one of the artists that inspired Miró?

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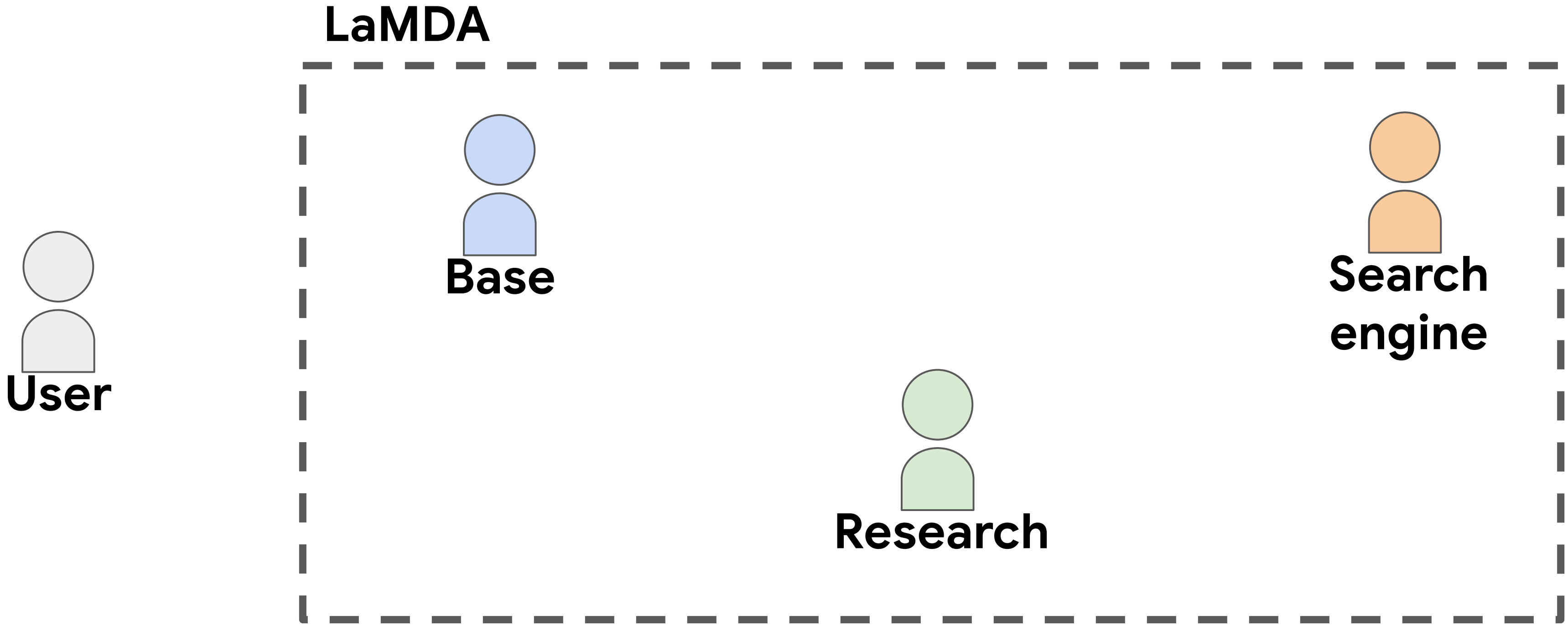
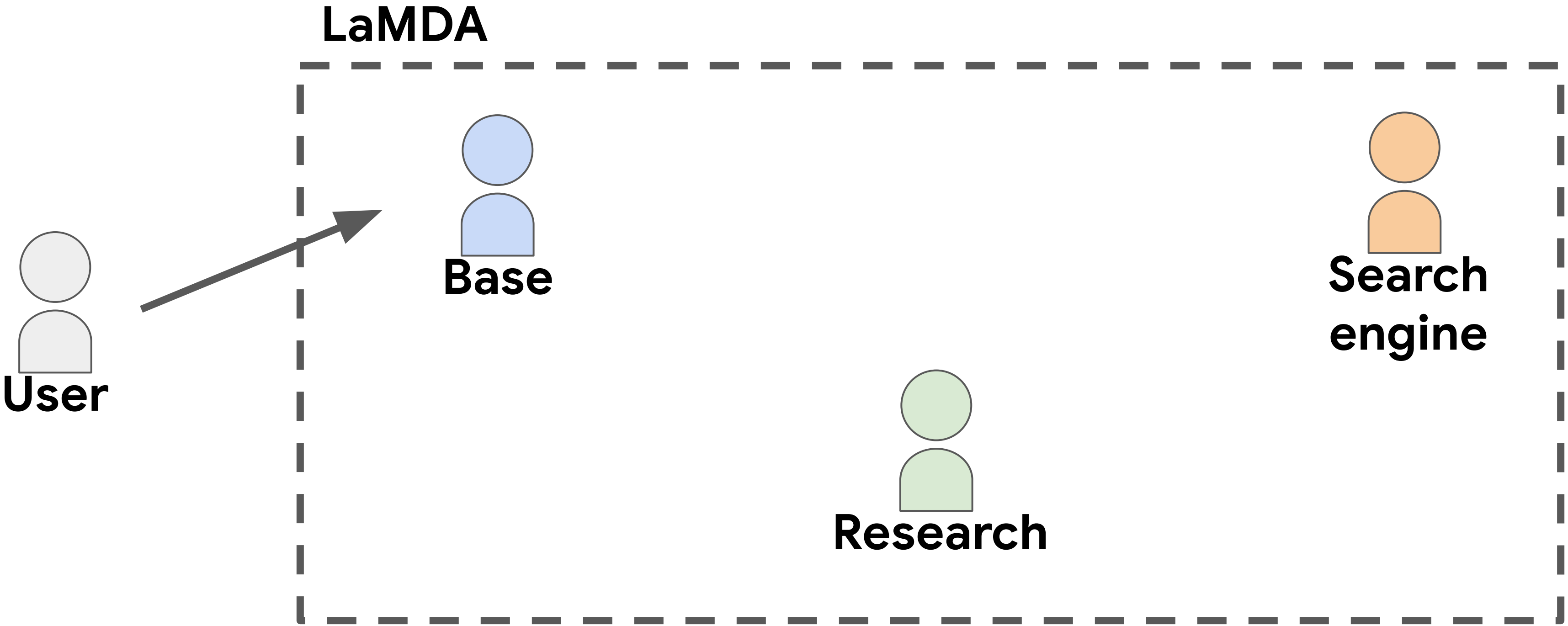
Solution: teach LaMDA to use a **search engine** to validate or fix its claims.

Using a search engine to improve factuality

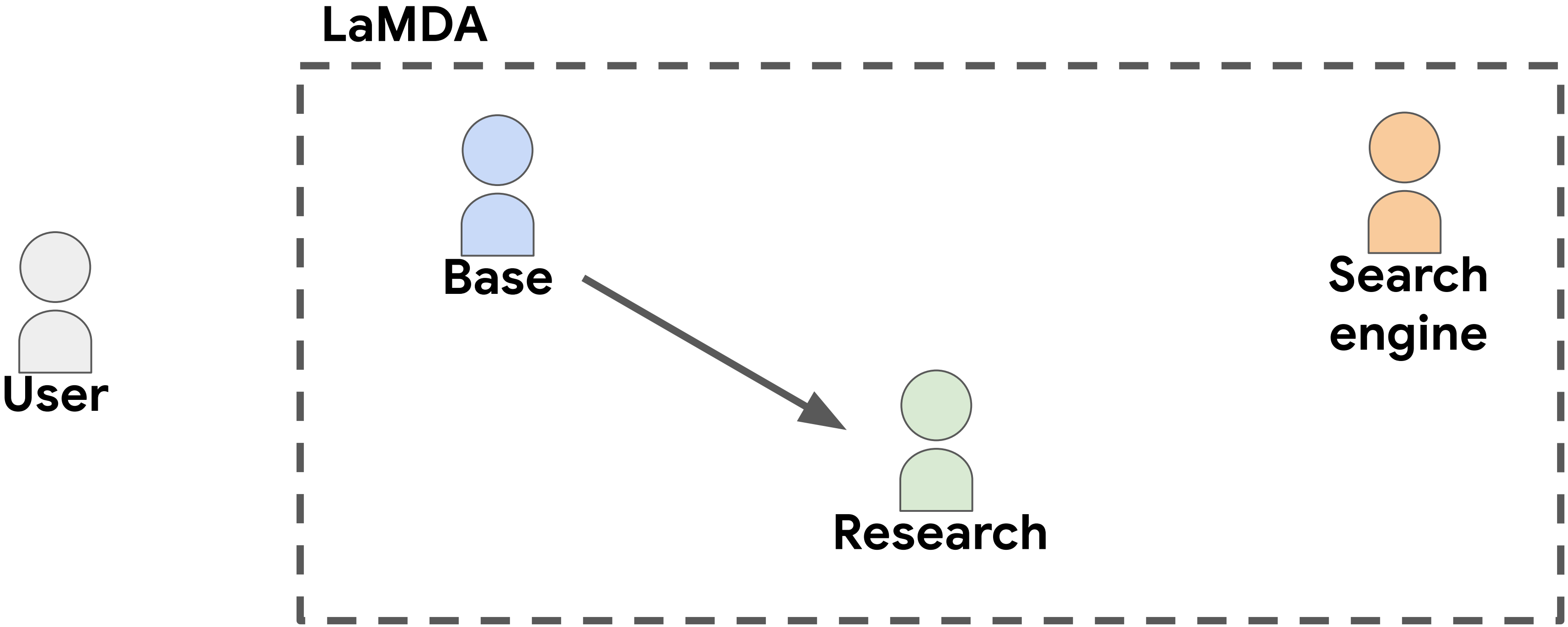


Using a search engine to improve factuality



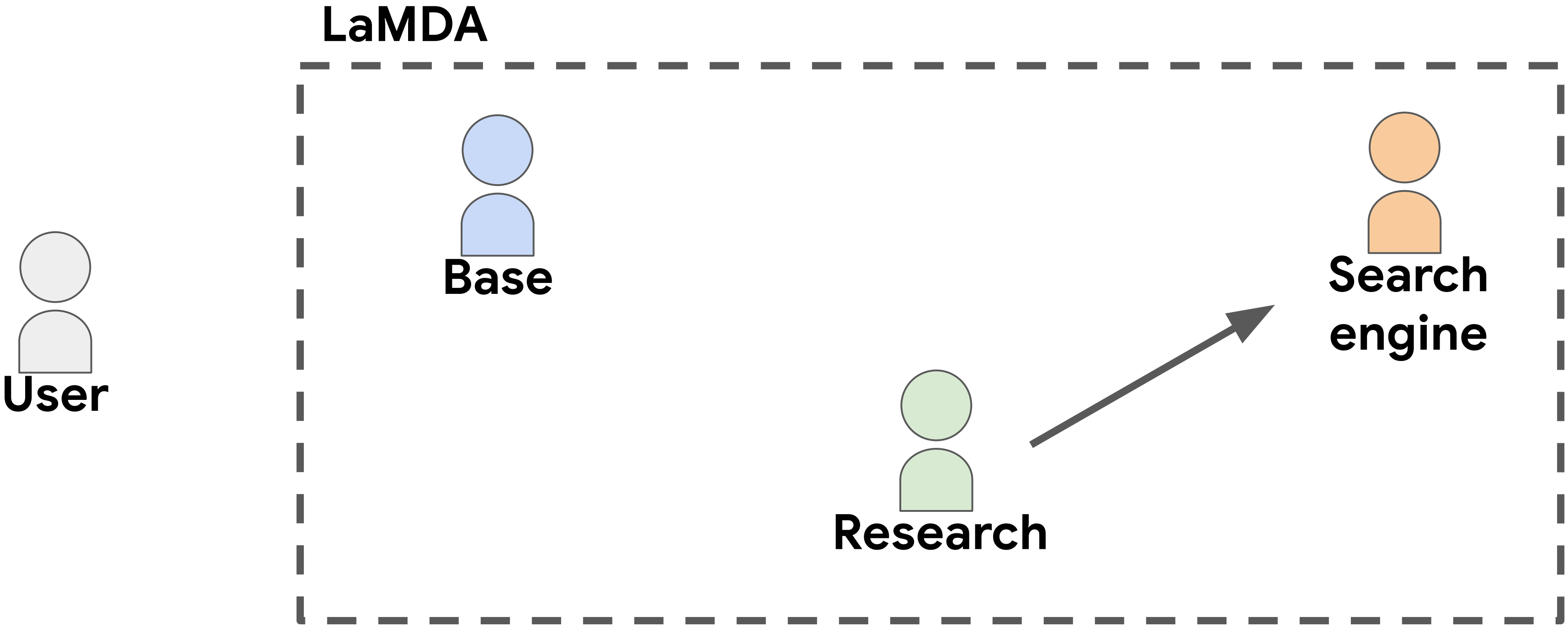
User to Base: When was the Eiffel Tower built?

Using a search engine to improve factuality



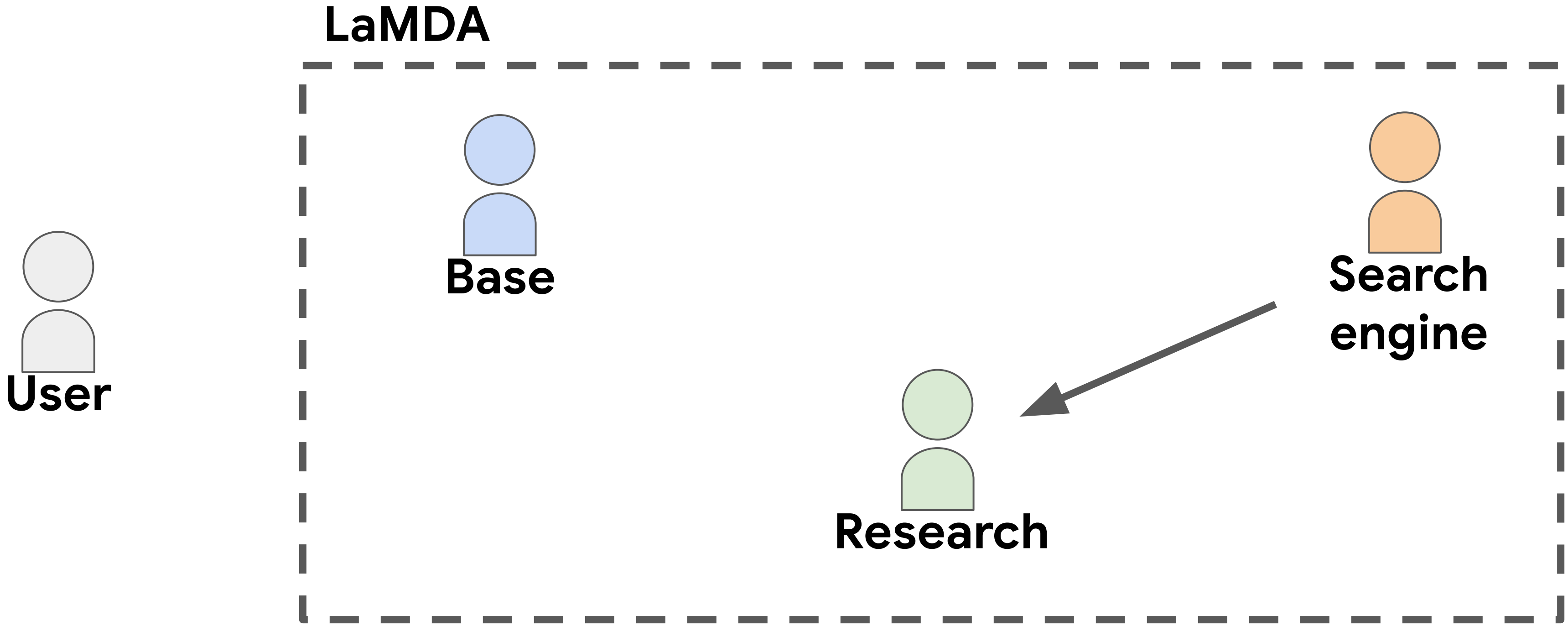
Base to Research: `It was constructed in` **1887**.

Using a search engine to improve factuality



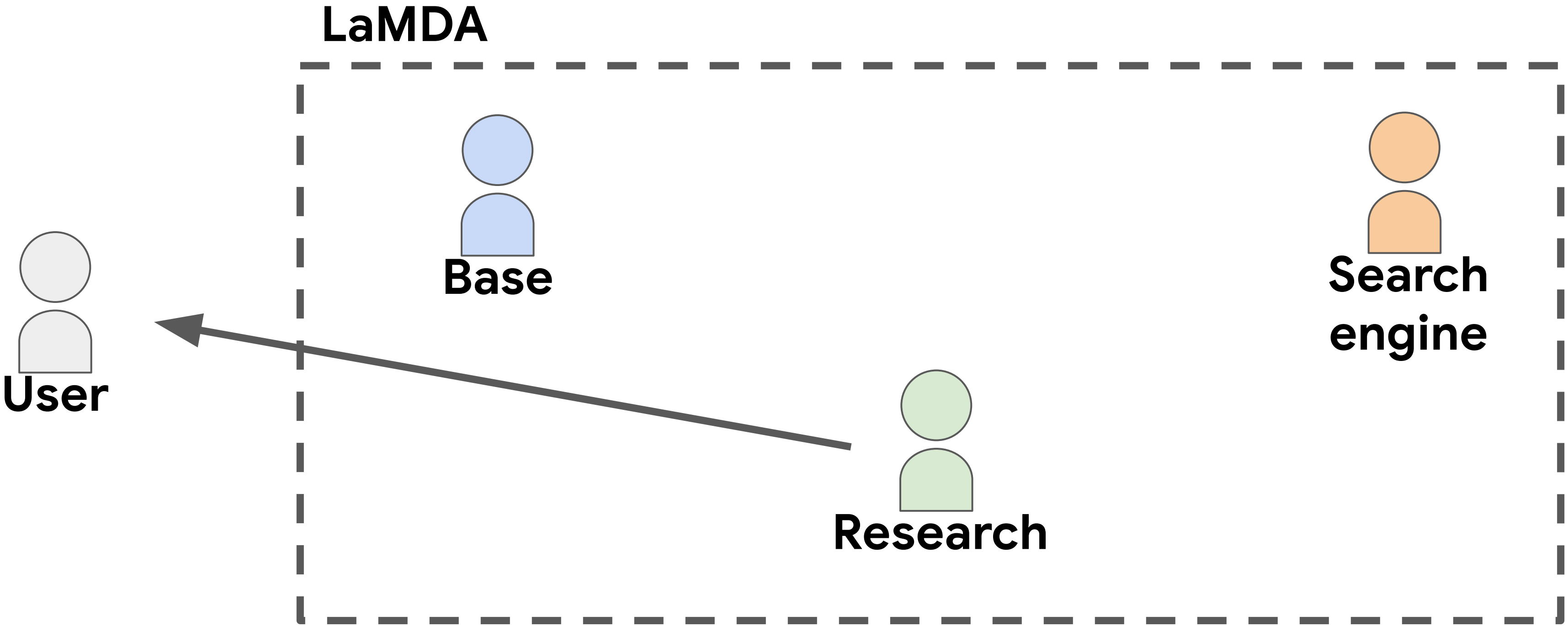
```
**Research to Search:** Eiffel Tower construction date
```

Using a search engine to improve factuality



Search to Research: 15 essential things to know about the Eiffel Tower | The Eiffel Tower was built in record time: 2 years, 2 months and 5 days. From late January 1887 to **March 31, 1889**. In addition to the technical … | https://www.toureiffel.paris

Using a search engine to improve factuality



Research to User: Work started on it in January 1887 and it was opened in March 1889.

Modeling: just treat everything as dialog

- **Input**
  - **User:** Base, When was the Eiffel Tower built?
  - **Base:** Research, It was constructed in 1887.
  - **Research:** Search engine, Eiffel Tower construction date
  - **Search engine:** Research, 15 essential things to know about the Eiffel Tower |
  - The Eiffel Tower was built in record time: 2 years, 2 months and 5 days. From late January 1887 to March 31, 1889…
- **Output**
  - **Research:** User, Work started on it in January 1887 and it was opened in March 1889.

On each turn, the utterance is addressed to one of the agents (User / Base / Research / Search engine). That is the agent who responds next.

Modeling: just treat everything as dialog

- **Input**
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  - **Base:** Research, It was constructed in 1887.
  - **Research:** Search engine, Eiffel Tower construction date
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  - The Eiffel Tower was built in record time: 2 years, 2 months and 5 days. From late January 1887 to March 31, 1889…
- **Output**
  - **Research:** User, Work started on it in January 1887 and it was opened in March 1889.

Both **input** and **output** are just text.

We can train a **standard Transformer decoder** to do this.

Modeling: just treat everything as dialog

- Input
  - `**User:** Base, When was the Eiffel Tower built?`
  - `**Base:** Research, It was constructed in 1887.`
  - `**Research:** Search engine, Eiffel Tower construction date`
  - `**Search engine:** Research, 15 essential things to know about the Eiffel Tower |`
  - `The Eiffel Tower was built in record time: 2 years, 2 months and 5 days. From late January 1887 to March 31, 1889…`
- Output
  - `**Research:** User, Work started on it in January 1887 and it was opened in March 1889.`

Where do we get dialog data like this to train on?

- Human crowdworkers play the role of **User** and **Research**.
- **Base** is a basic Transformer chatbot.
- **Search engine** is something like Google Search.

Modeling: just treat everything as dialog

- **Input**
  - **User:** Base, When was the Eiffel Tower built?
  - **Base:** Research, It was constructed in 1887.
  - **Research:** Search engine, Eiffel Tower construction date
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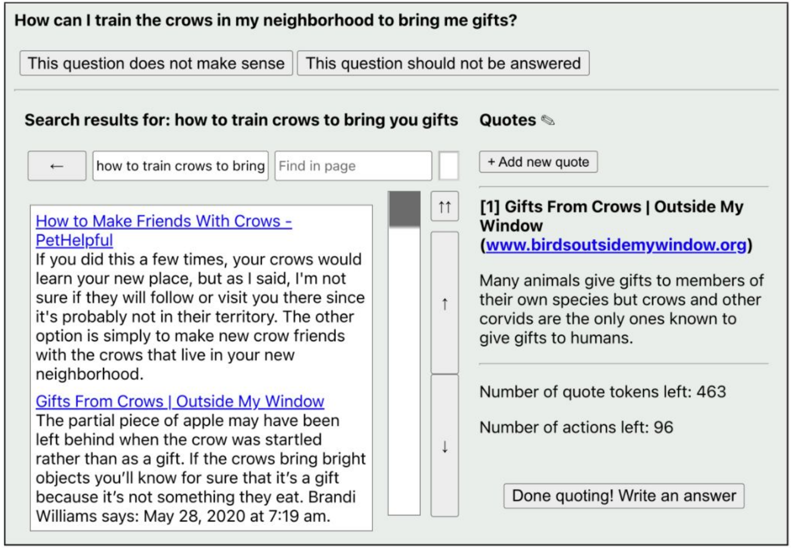
  - The Eiffel Tower was built in record time: 2 years, 2 months and 5 days. From late January 1887 to March 31, 1889…
- **Output**
  - **Research:** User, Work started on it in January 1887 and it was opened in March 1889.

LaMDA learns to **reformulate** the user's question as a search query.

LaMDA learns to **incorporate knowledge** from search results.

Another model that uses external tools

(**WebGPT**: Nakano et al, 2021)



How can I train the crows in my neighborhood to bring me gifts?

This question does not make sense
This question should not be answered

Search results for: how to train crows to bring you gifts

←
how to train crows to bring
Find in page
↑↑
↑
↓

How to Make Friends With Crows - PetHelpful
If you did this a few times, your crows would learn your new place, but as I said, I'm not sure if they will follow or visit you there since it's probably not in their territory. The other option is simply to make new crow friends with the crows that live in your new neighborhood.

Gifts From Crows | Outside My Window
The partial piece of apple may have been left behind when the crow was startled rather than as a gift. If the crows bring bright objects you'll know for sure that it's a gift because it's not something they eat. Brandi Williams says: May 28, 2020 at 7:19 am.

Quotes

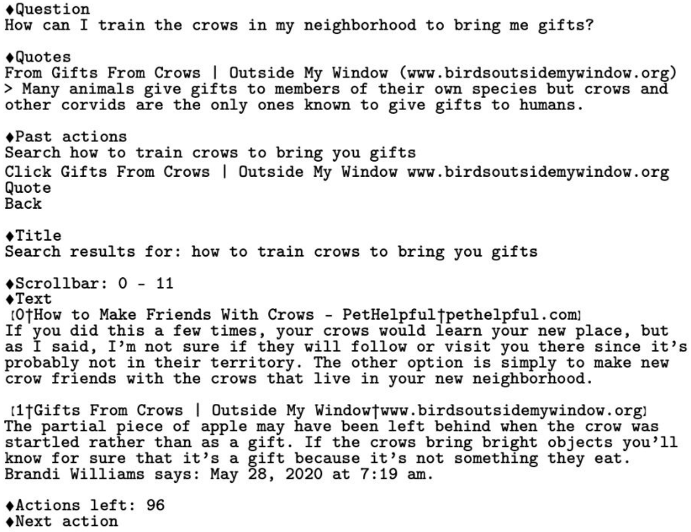
[1] Gifts From Crows | Outside My Window (www.birdsoutsidemywindow.org)

Many animals give gifts to members of their own species but crows and other corvids are the only ones known to give gifts to humans.

Number of quote tokens left: 463

Number of actions left: 96

(a) Screenshot from the demonstration interface.



```
♦Question
How can I train the crows in my neighborhood to bring me gifts?

♦Quotes
From Gifts From Crows | Outside My Window (www.birdsoutsidemywindow.org)
> Many animals give gifts to members of their own species but crows and
other corvids are the only ones known to give gifts to humans.

♦Past actions
Search how to train crows to bring you gifts
Click Gifts From Crows | Outside My Window www.birdsoutsidemywindow.org
Quote
Back

♦Title
Search results for: how to train crows to bring you gifts

♦Scrollbar: 0 - 11
♦Text
【0†How to Make Friends With Crows - PetHelpful†pethelpful.com】
If you did this a few times, your crows would learn your new place, but
as I said, I'm not sure if they will follow or visit you there since it's
probably not in their territory. The other option is simply to make new
crow friends with the crows that live in your new neighborhood.

【1†Gifts From Crows | Outside My Window†www.birdsoutsidemywindow.org】
The partial piece of apple may have been left behind when the crow was
startled rather than as a gift. If the crows bring bright objects you'll
know for sure that it's a gift because it's not something they eat.
Brandi Williams says: May 28, 2020 at 7:19 am.

♦Actions left: 96
♦Next action
```

(b) Corresponding text given to the model.

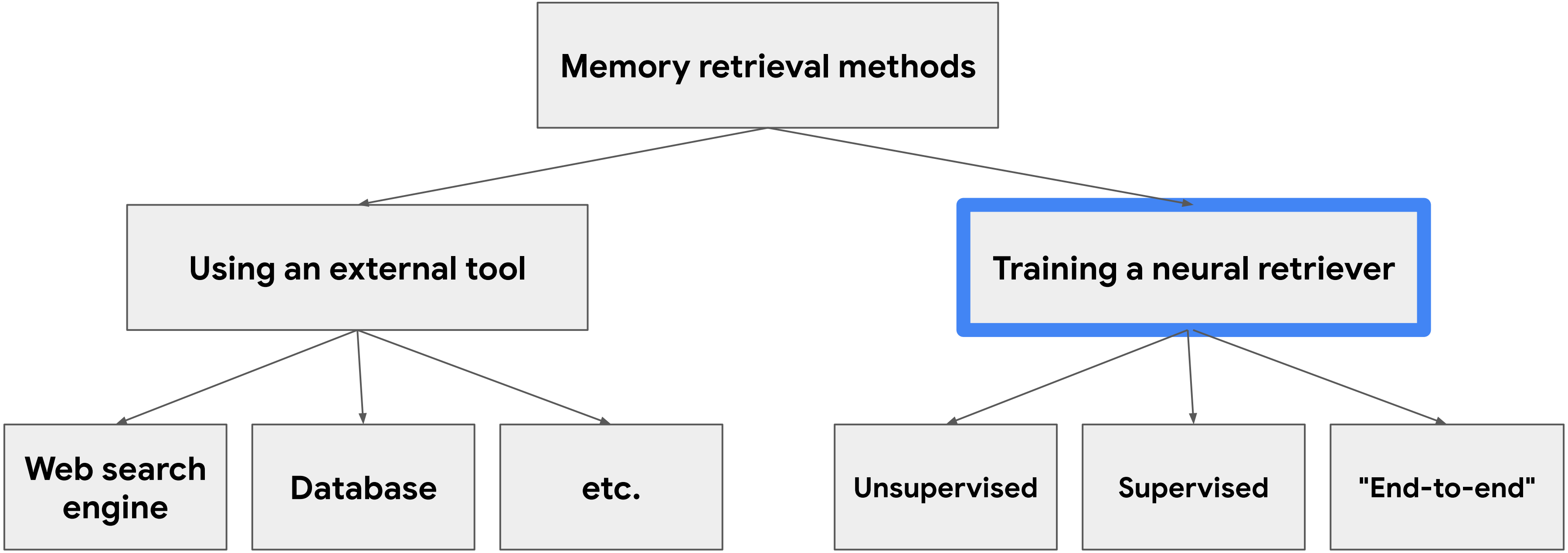
Main takeaways

- Many external retrieval tools accept **text** as input and return **text** as output.
- So, learning to use an external tool boils down to:
  - 1) Learning to **generate text queries** to the tool.
  - 2) Learning to **understand the text output** of the tool.
- Both tasks can be handled by a standard Transformer model.
- Current approaches train on demonstrations from humans.
  - (Approaches like WebGPT also add some RL training)

We can query web search! Why use anything else?

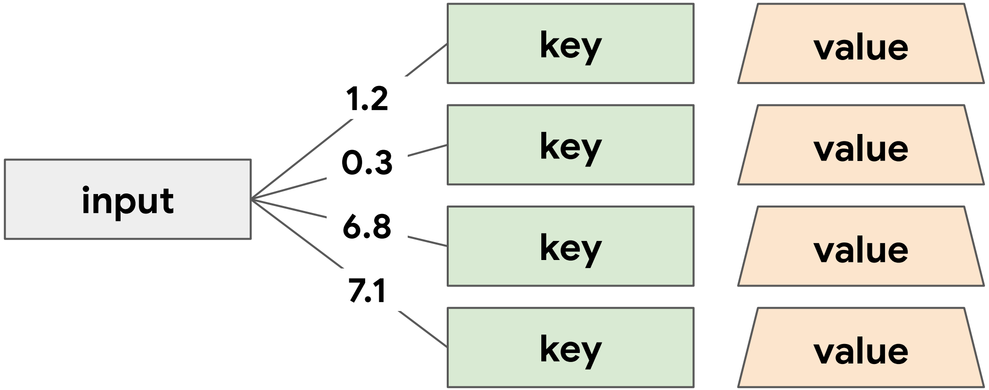
- Web search is far from perfect. New research is what makes it better!
  - "famous lawyer who got into car accident" → [only returns car accident lawyers]
  - "use nlp to parse research papers" → [mostly nlp papers on parsing]
  - Also, try searching in other languages.
- Web search can't handle everything
  - **Doctor:** Given a medical image, retrieve similar images from medical textbooks?
  - **Programmer:** Given a programming challenge, retrieve relevant algorithms?
  - **Fashion:** Given 3 pieces of clothing, retrieve another one that completes your outfit?
  - **Novelist:** Given a story, retrieve other stories with the same plot?
  - **Journalist:** Given a claim, retrieve news articles that contradict it?
- Web search just can't access non-public data
  - Collecting human demonstrations to interface with each non-public tool -- expensive!

An overview


Memory retrieval methods
Using an external tool
Training a neural retriever
Web search engine
Database
etc.
Unsupervised
Supervised
"End-to-end"

Anatomy of a neural retriever

1. Score the **input** against each **key**.
2. Return the **value** for the highest scoring key.



Anatomy of a neural retriever

1. Score the **input** against each **key**.
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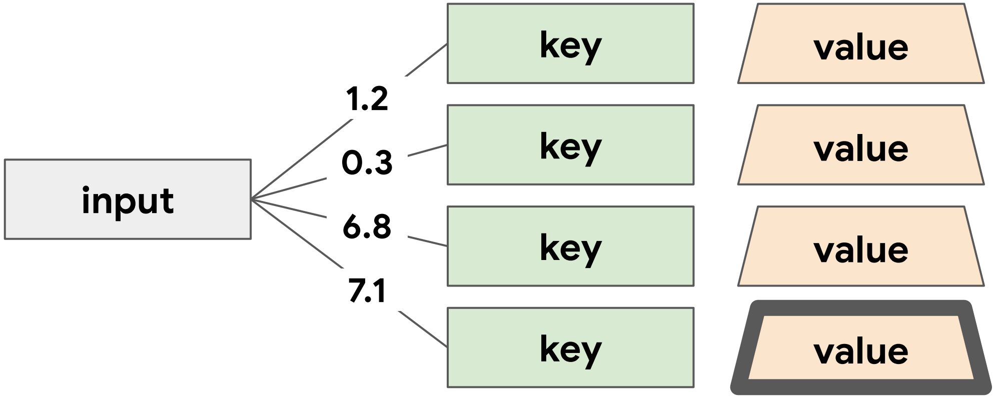
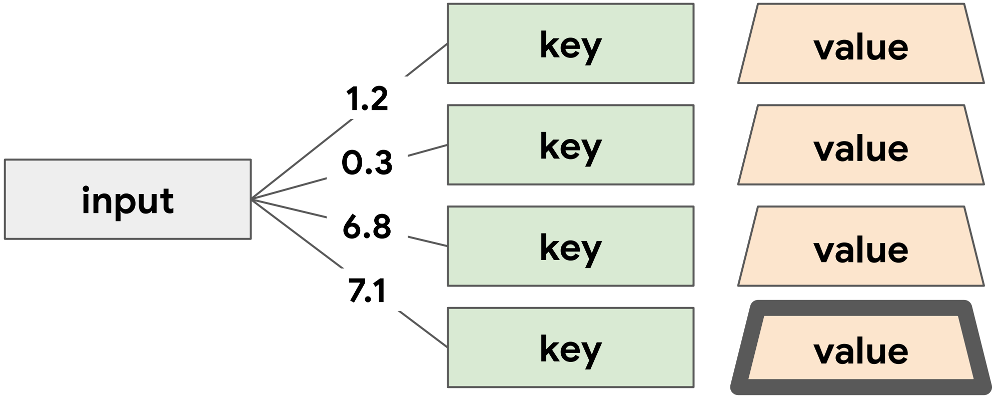


Example:

input = "Eiffel Tower location" **key =** <document title> **value =** <document text>

Anatomy of a neural retriever

1. Score the **input** against each **key**.
2. Return the **value** for the highest scoring key.

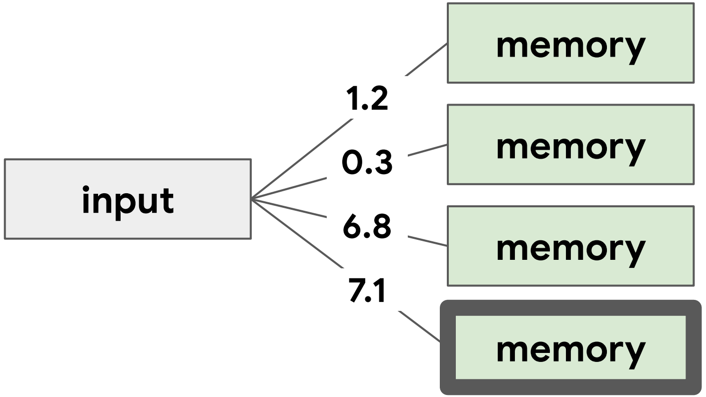


A **retriever** is just a function: `f(input, key) → score`

Simplified setup

In many tasks, key == value. We just call it a "memory" then.

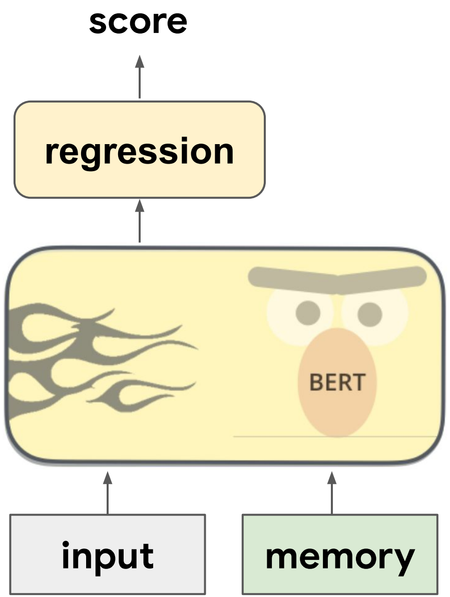
1. Score the **input** against each **memory**.
2. Return the **highest scoring memory**.



A **retriever** is just a function: **`f(input, memory) → score`**

What are common retrieval scoring functions?

```
f(input, memory) → score
```



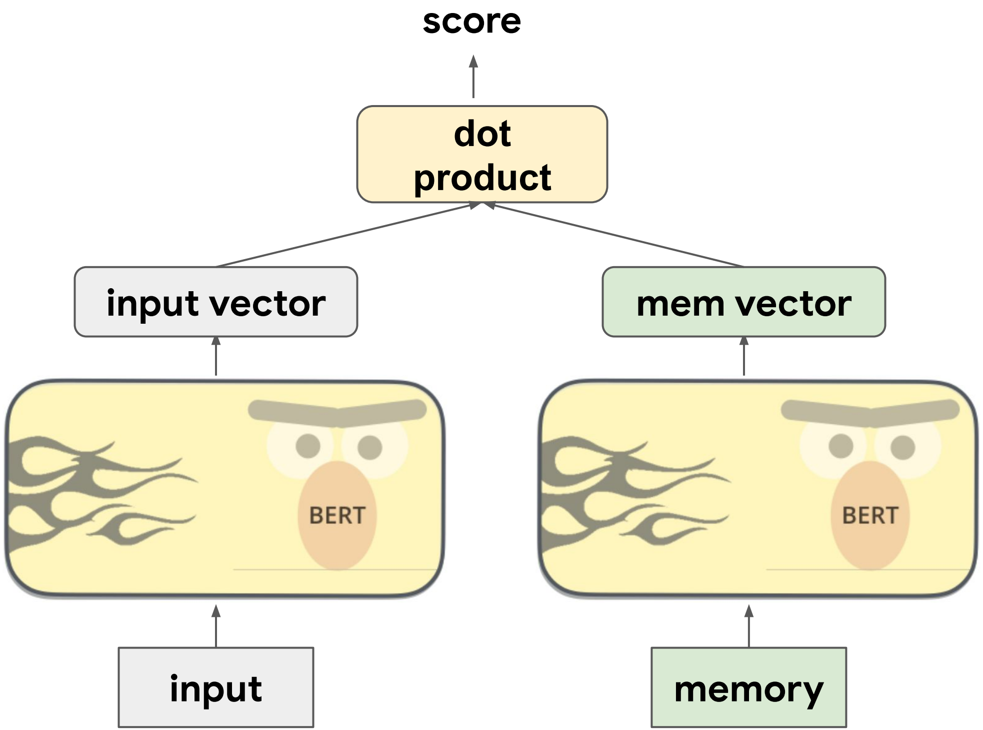
Advantages:

- Using a powerful Transformer model to compare the input against each memory.
- Differentiable -- can optimize with gradient descent.

Disadvantages:

- For each new input, you have to do this comparison against EVERY memory.
- Too slow if you have **millions of memories**.

What are common retrieval scoring functions?



Advantages:

- Can precompute all memory vectors.
- Only have to do this **once**, NOT for every input.
- Computing a simple dot product is fast.
- Differentiable -- can optimize with gradient descent.

Disadvantages:

- Dot product is not very expressive.

Training a neural retriever (supervised learning)

```
f(input, memory) → score
```

Training data:

```
input = "Eiffel Tower location"

positive = "Where To Find The Eiffel Tower…"

negatives:
```

- `negative_1 = "Where Super Bowl Is This Year…"`
- `negative_2 = "Sears Tower Location…"`
- `…`

$$s^* = f(\text{input}, \text{positive})$$

$$s_i = f(\text{input}, \text{negative\_i})$$

$$p(\text{positive}) = \frac{\exp(s^*)}{\exp(s^*) + \sum_i \exp(s_i)}$$

$$\text{maximize} \;\; \log p(\text{positive})$$

A concrete example (**DPR**: Karpukhin et al, 2020)

Task:

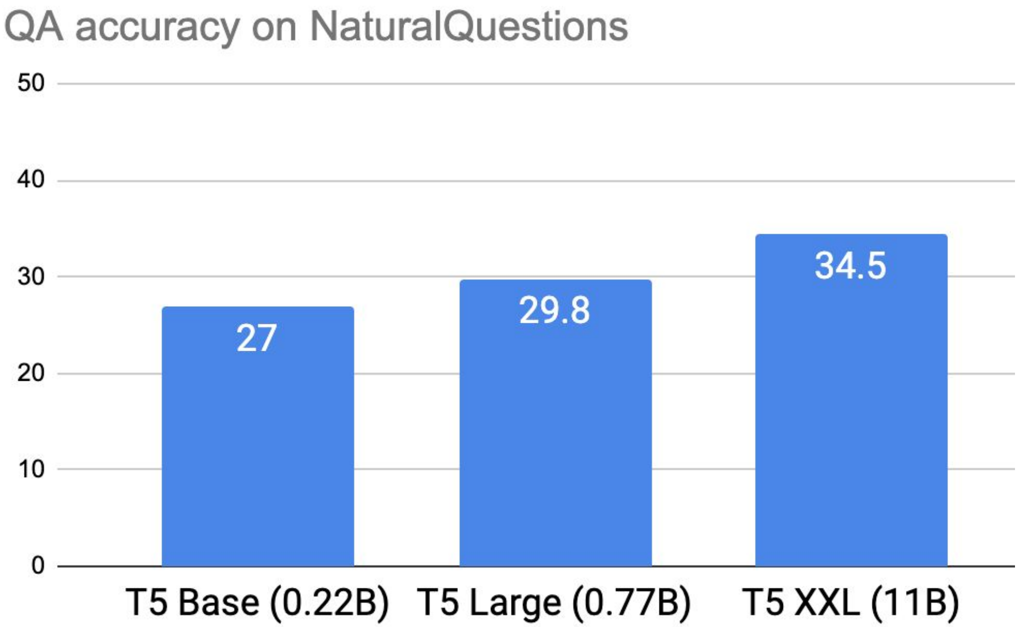
- Given a **query** "Who is the bad guy in lord of the rings?"
- Retrieve a **passage** from Wikipedia containing the answer.
- Read the retrieved passage and produce the **answer** ⟶ Sauron.

Training data for retriever:

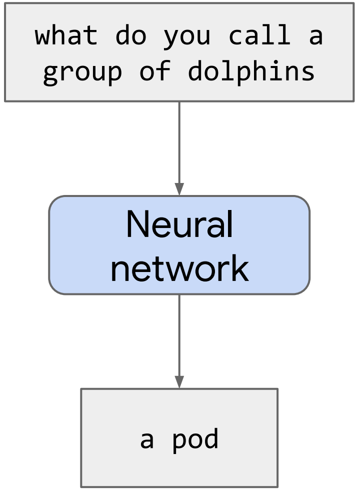
- NaturalQuestions dataset contains **(query, passage, answer)** examples.

- **input** = query
- **positive memory** = passage
- **negative memories** =
  - The positive passages for ***other*** queries.
  - A passage retrieved by an off-the-shelf search tool (BM25), that does NOT contain the **answer**.

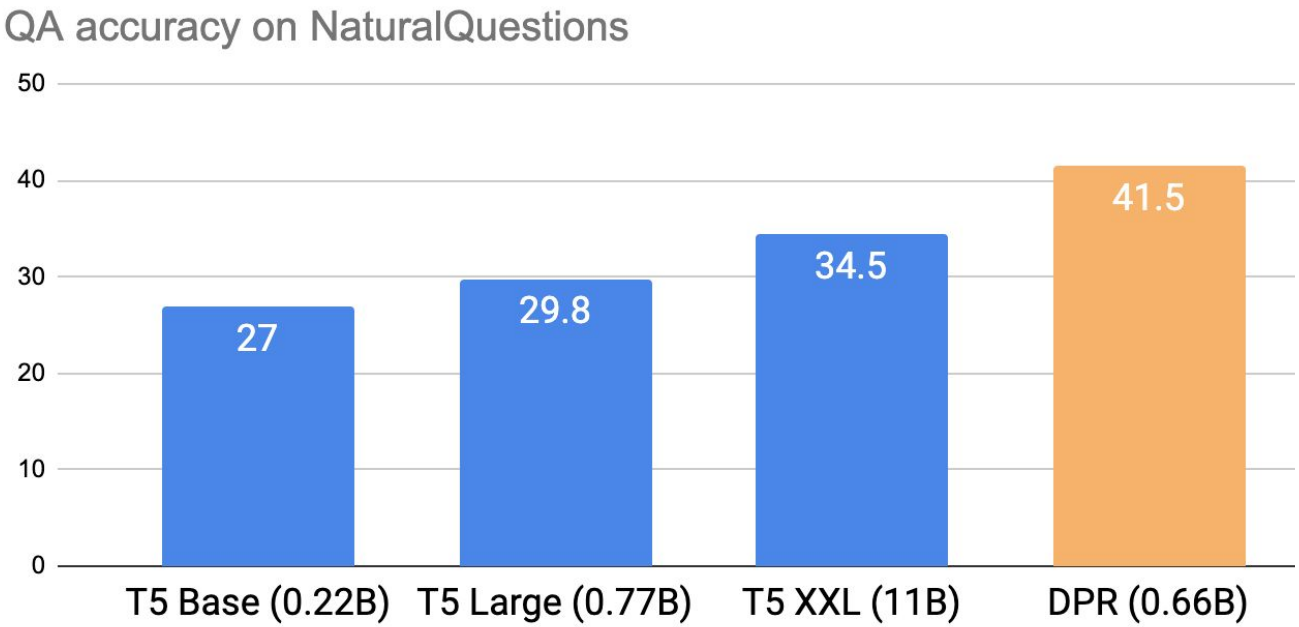
How well does it work?



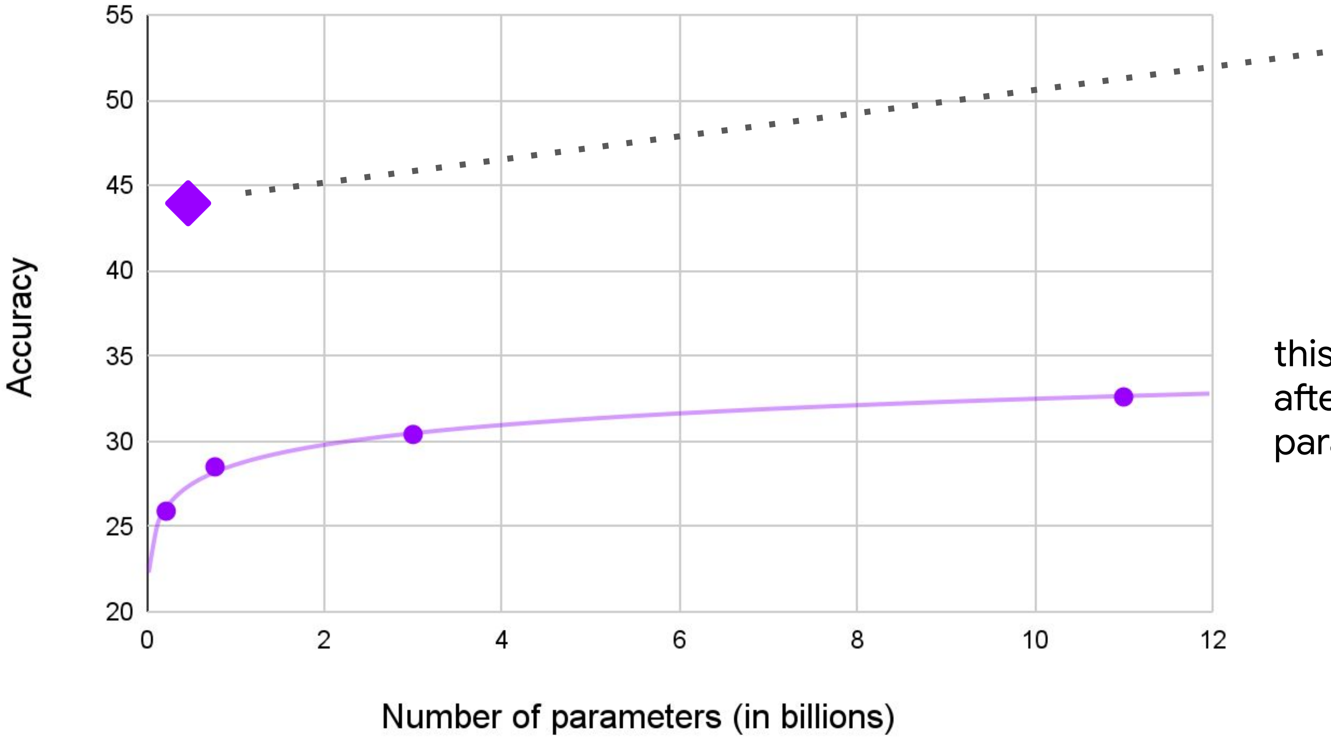
standard seq2seq Transformer (T5)
(no external memory)



How well does it work?



Well, maybe just need to make T5 bigger?



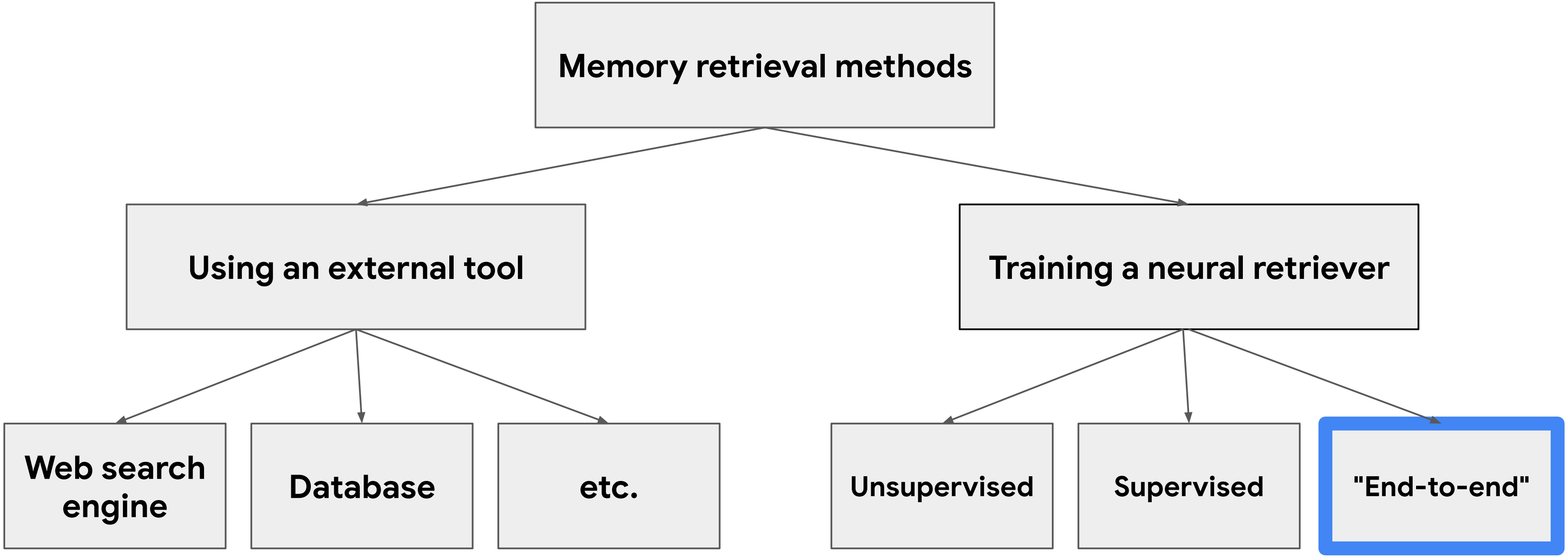
DPR has better accuracy with fewer parameters.

this line barely hits 40 after **8 trillion** parameters

What if you don't have training data for the retriever?

- In the previous example, we had a dataset with **(query, passage, answer)** examples.
- But what if the examples were just **(query, answer)**?
- How can we train a retriever without gold passages?
- This problem arises in other tasks too:
    - Natural language ⟶ code (retrieve code snippets)
    - Medical symptoms ⟶ diagnosis (retrieve medical knowledge)

An overview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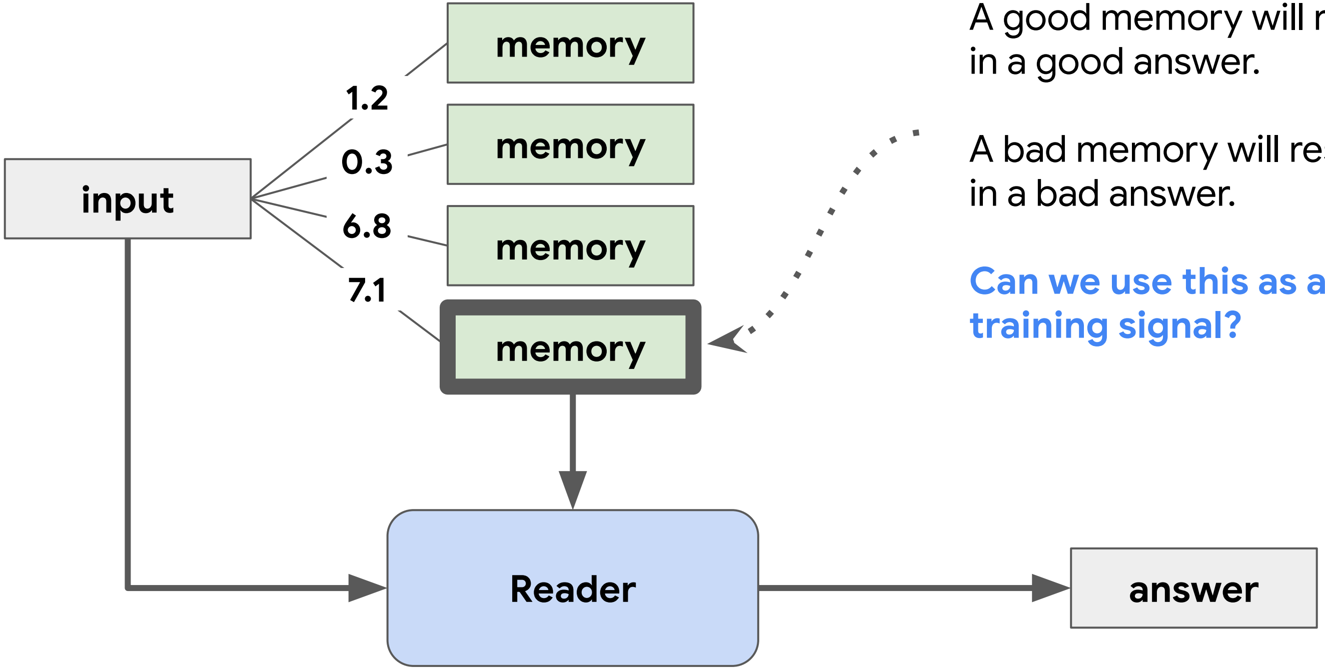
End-to-end learning

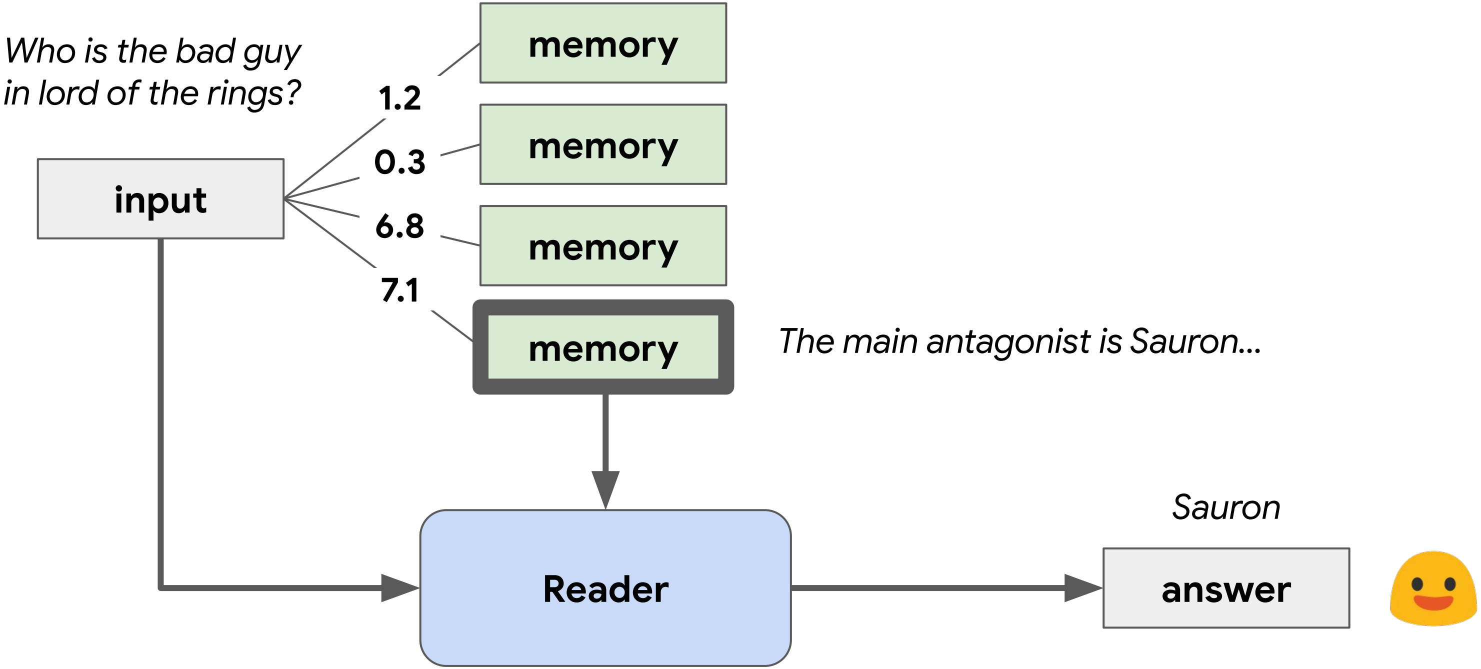


A good memory will result in a good answer.

A bad memory will result in a bad answer.

Can we use this as a training signal?

End-to-end learning



Who is the bad guy in lord of the rings?

input

1.2

0.3

6.8

7.1

memory

memory

memory

memory

The main antagonist is Sauron...

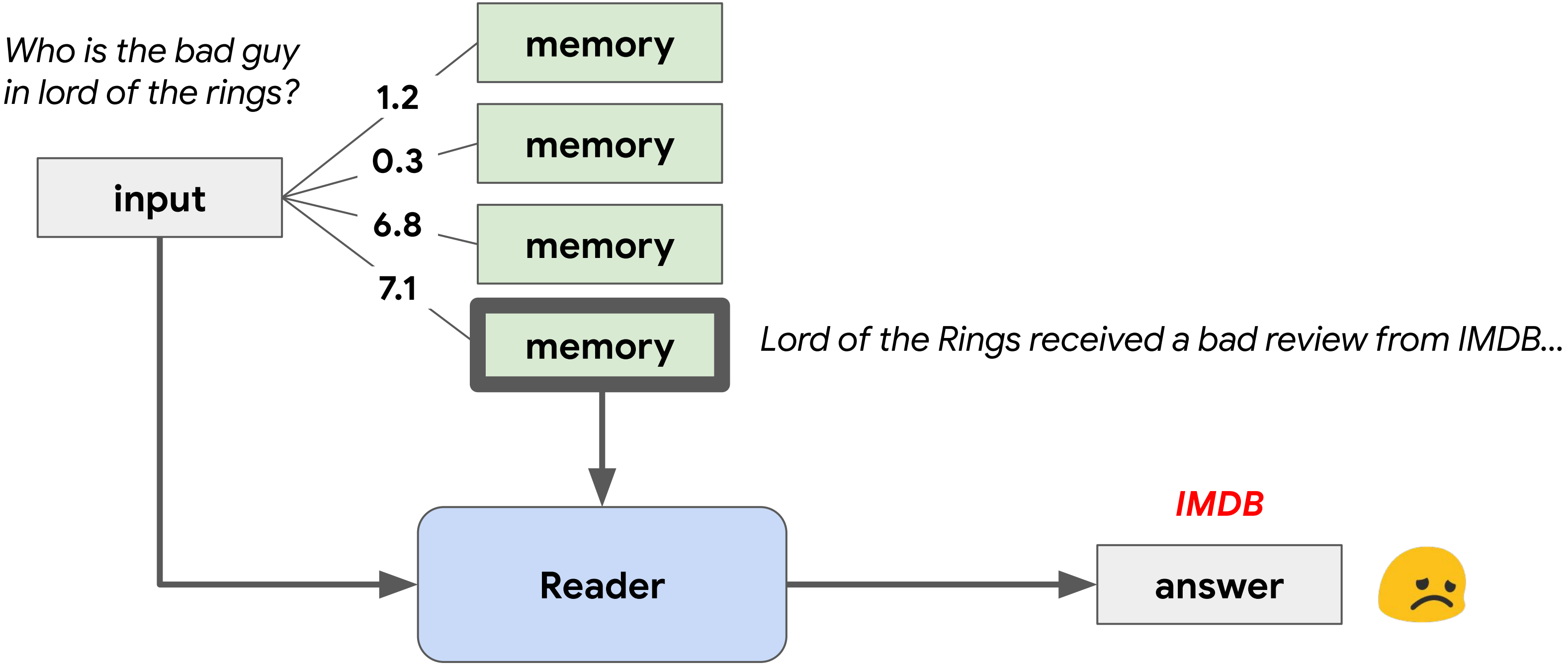
Reader

Sauron

answer

😃

End-to-end learning


Who is the bad guy in lord of the rings?
input
1.2
0.3
6.8
7.1
memory
memory
memory
memory
Lord of the Rings received a bad review from IMDB...
Reader
IMDB
answer
😟

Intuitive idea (**trial and error**)

- **Exploration**
  - Use our (imperfect) retriever to select a memory.
  - **Try** feeding that memory to the Reader.
- **Learn from success / failure**
  - If the memory **helps** the Reader generate the right answer
    → **increase its retrieval score.**
  - If the memory **does not help** the Reader generate the right answer
    → **decrease its retrieval score.**

Over time, helpful memories get the highest scores.

Formal idea (**ORQA:** Lee et al, 2019)

Exploration

- A retriever is just a scoring function, **f(input, memory) ⟶ score.**
- Take softmax over all memory scores:

$$p(\text{memory} \mid \text{input}) = \frac{\exp f(\text{input}, \text{memory})}{\sum_i \exp f(\text{input}, \text{memory\_i})}$$

- Randomly sample a memory from this distribution.

Formal idea

Learn from success / failure

- Once we pick a memory, see if it helps.
- **Reader's probability of generating right answer:**

$$p(\mathrm{gold\_answer} \mid \mathrm{input}, \mathrm{memory})$$

- If high → **increase** retrieval score of this memory.
- If low → **decrease** retrieval score of this memory.

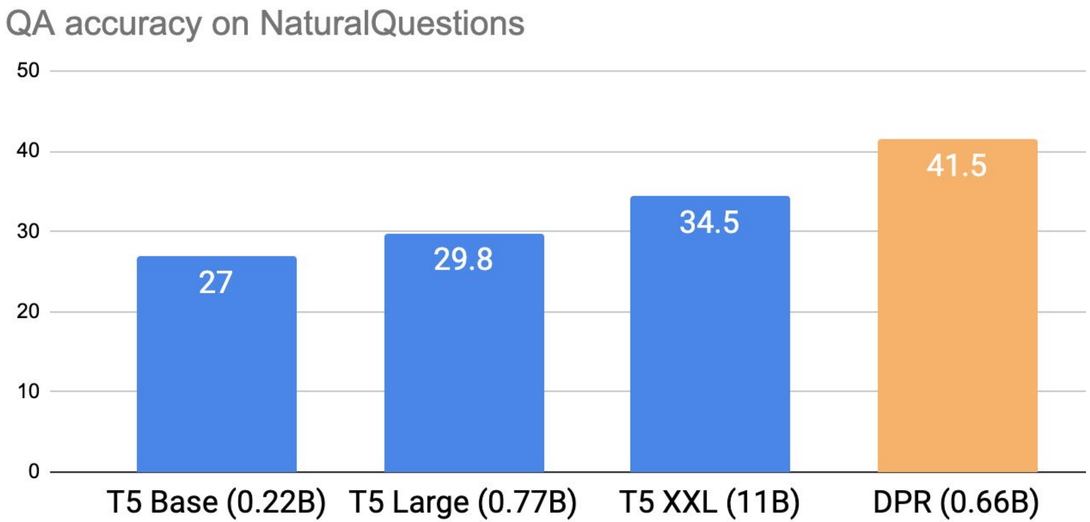
Formal idea

- If we randomly sample a memory and then generate an answer... what is the probability that we get the answer right?

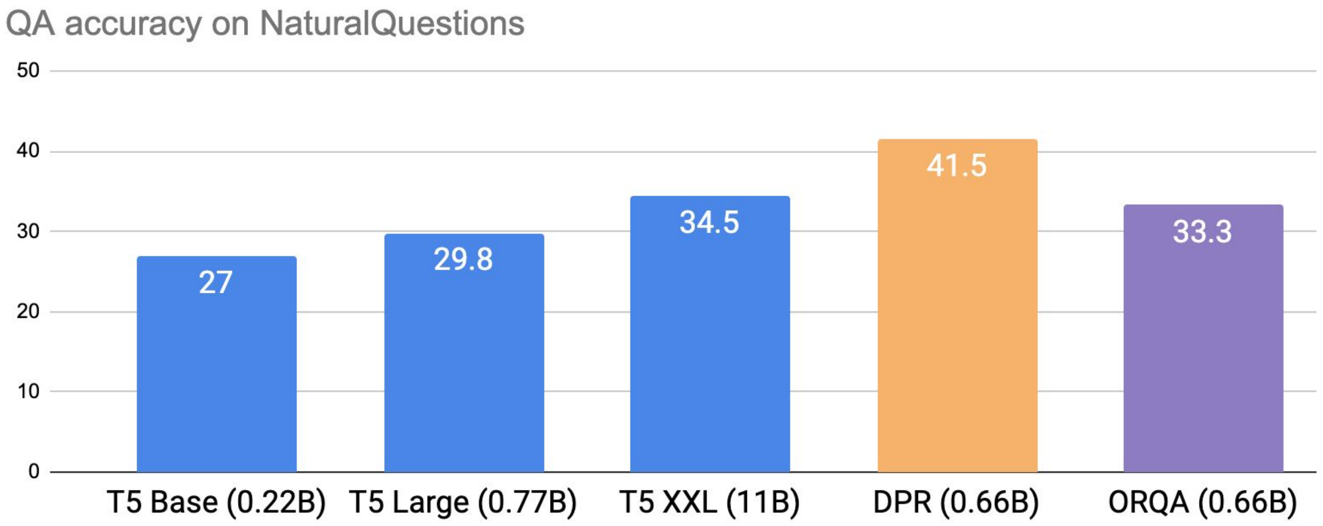
$$\sum_{\text{memory}} p(\underbrace{\text{memory} \mid \text{input}}_{\substack{\textbf{Retriever:} \\ \text{propose memory}}})\ \underbrace{p(\text{gold\_answer} \mid \text{input}, \text{memory}}_{\substack{\textbf{Reader:} \\ \text{succeed or fail}}})$$

- Each term in this summation is a **"trial"** of a different memory.
- Some memories will **succeed**, others won't.
- **ORQA: Use gradient descent to maximize this quantity** (more precisely, the log of this)
- $p(\text{memory} \mid \text{input})$ will naturally place its mass on good memories.

How well does it work?



How well does it work?



needs
gold passages

outperforms T5 at same size.
near T5 @ **15x** larger size.

(query, answer) pairs are weaker signal than **(query, passage, answer)**.

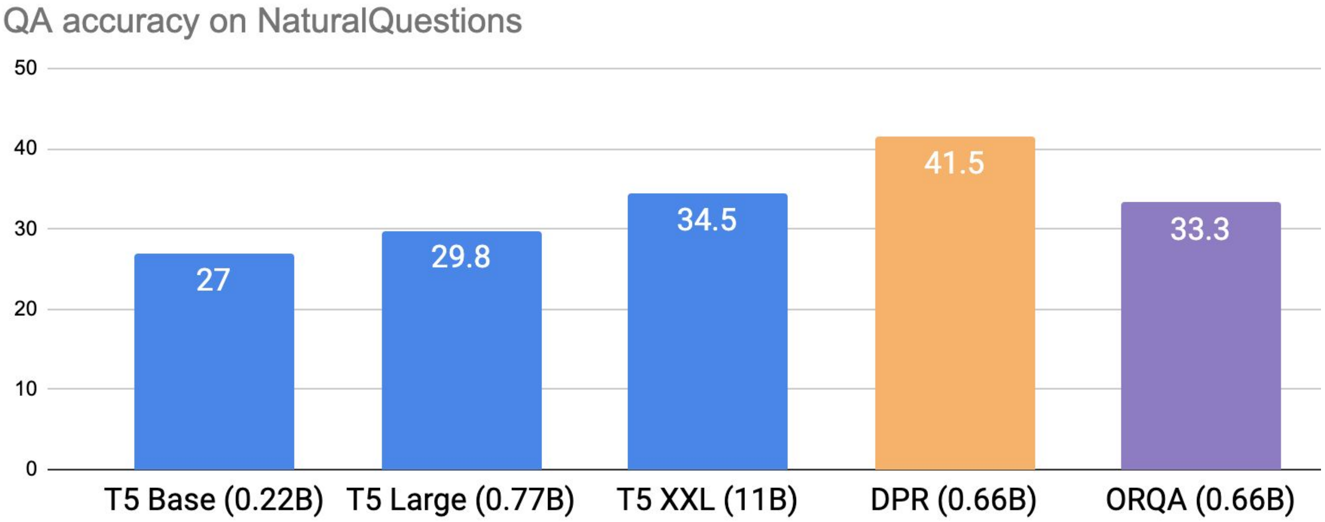
But it is easier to find (query, answer) data -- maybe we can get more of it?

A way to get countless **(query, answer)** pairs

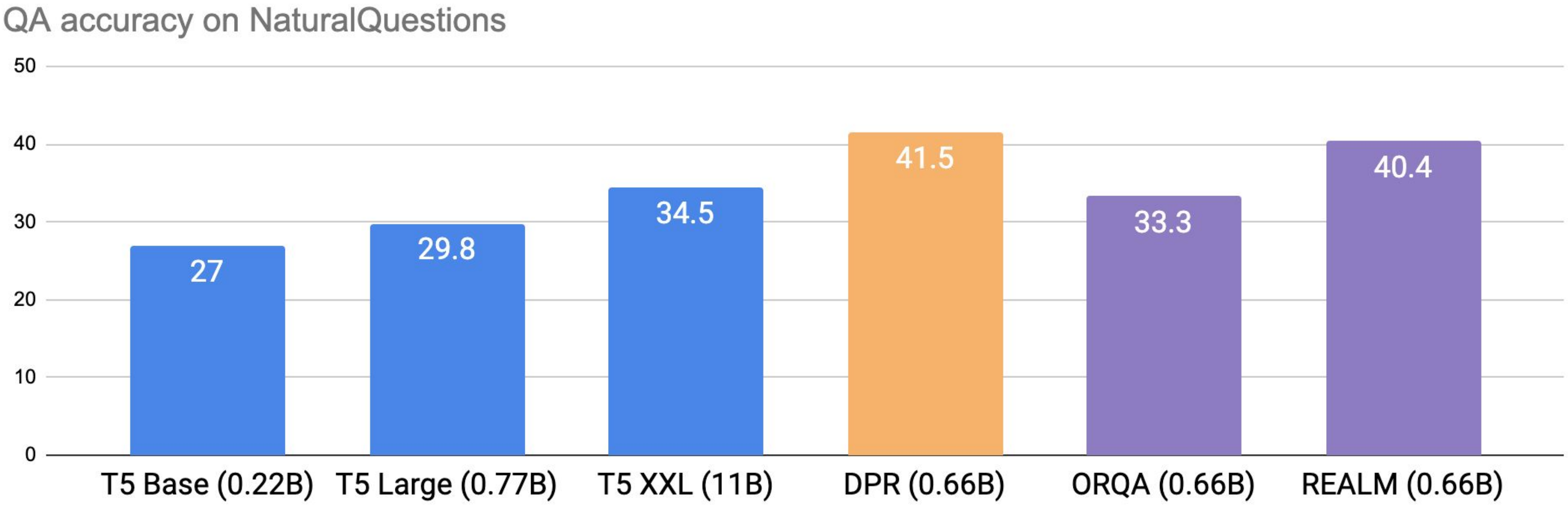
(**REALM:** Guu et al, 2020)

- **Typical (query, answer) pair:**
    - `"Who is the bad guy in lord of the rings?"` → `"Sauron"`
- **Fill-in-the-blank format:**
    - `"The bad guy in lord of the rings is ______"` → `"Sauron"`
- It is easy to create fill-in-the-blank questions:
    - Just take any sentence, and blank out one of the entities.
    - `"The Eiffel Tower is located in the city of Paris"`
    - This is just like **BERT-style language model pre-training.**
- Use **end-to-end training** just like ORQA:
    - **Pre-train** on fill-in-the-blank questions
    - **Fine-tune** on real questions

How well does it work?



How well does it work?



pre-training on fill-in-the-blank questions

Almost completely closes the gap with DPR, despite **no gold passages.**

Outperforms pure Transformer model, using same data, fewer parameters.

Fill-in-the-blank applies to many tasks:

- Blank out a patch of an image
- Blank out a segment of code
- Blank out a chapter in a textbook
- ...

Each task produces a **memory retriever** specialized for that domain.

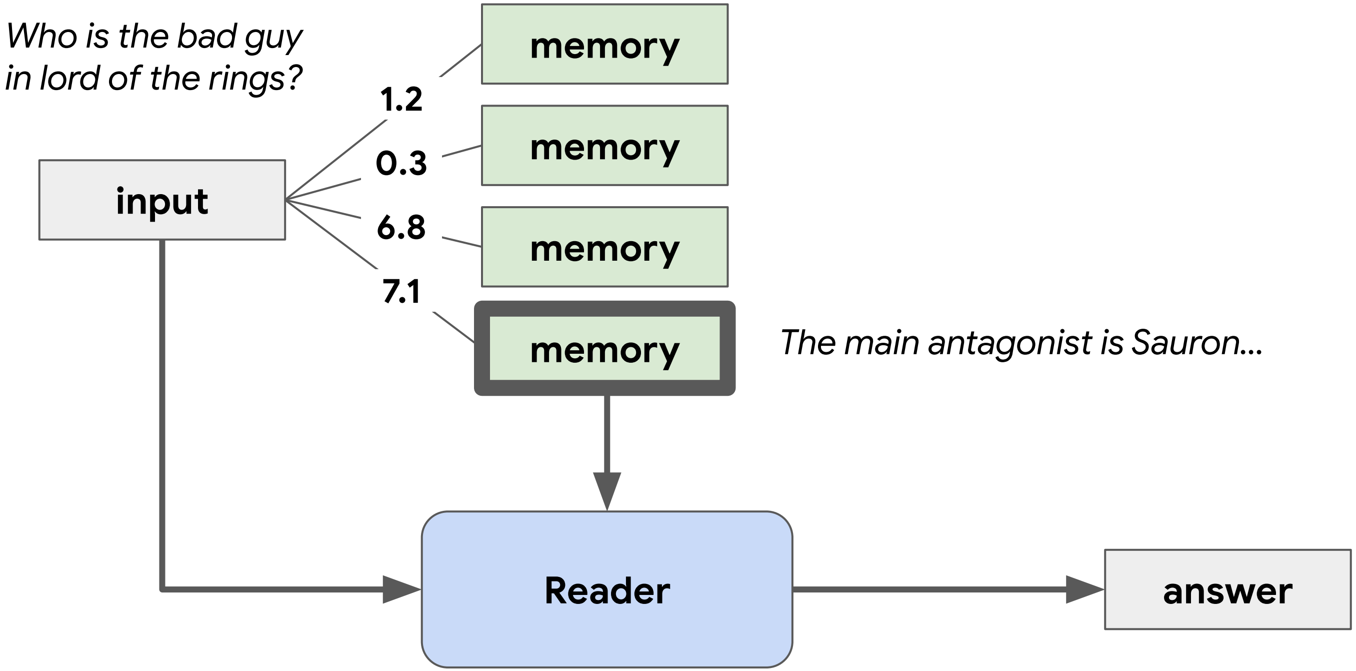
No need to collect any retrieval training data!

Main takeaways

- A retriever is a function, **f(input, memory) ⟶ score**
- **Supervised learning:**
  - For each input, provide **positive** memories and **negative** memories.
  - Train the retriever to score the positive ones higher.
- If you don't have supervision, use **end-to-end learning**
  - **Trial and error** approach: if a memory helps the model, score it higher.
- With end-to-end learning, you can often **create infinite data** using **fill-in-the-blank** training (aka language modeling).

How to use memories

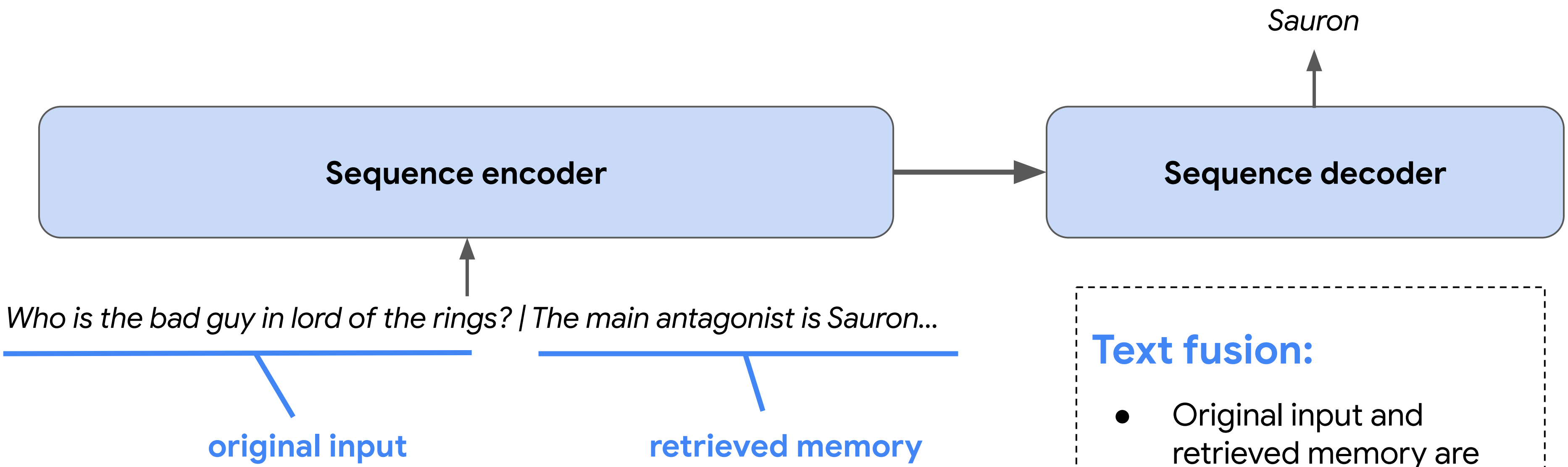
How to use memories?



Who is the bad guy in lord of the rings?

The main antagonist is Sauron...

Reader model

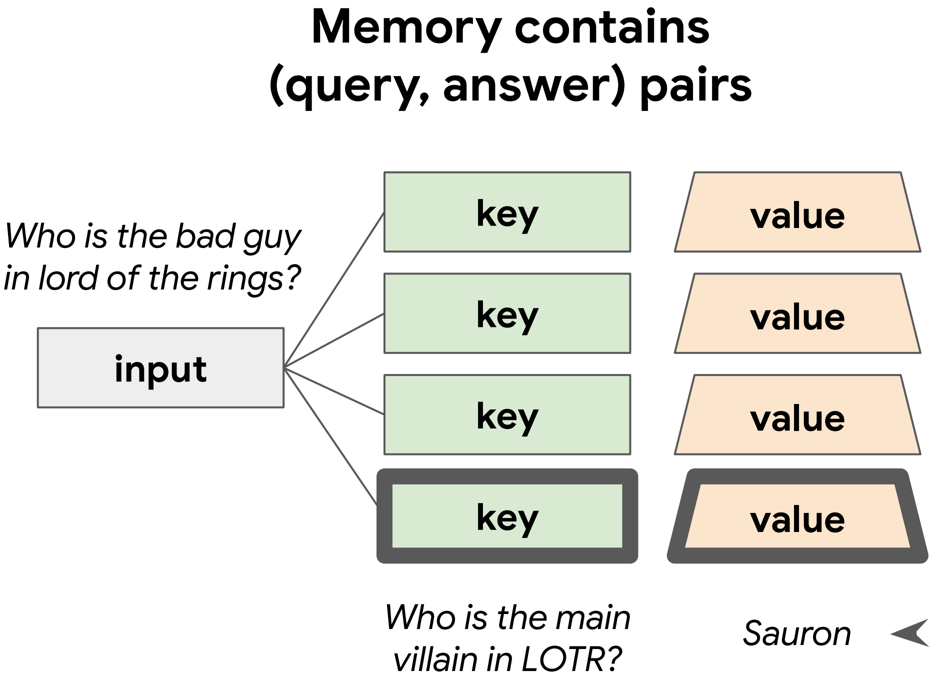

Sauron
Sequence encoder
Sequence decoder
Who is the bad guy in lord of the rings? | The main antagonist is Sauron...
original input
retrieved memory

Text fusion:

- Original input and retrieved memory are both text.
- Just concatenate them.

- **Input** is text, **output** is also text.
- Reader can be trained using standard **seq2seq** training.

Another way to incorporate memories



The input question looks similar to an existing question in the memory.

If they are similar enough, maybe they have the same answer.

Just copy this label as your answer.

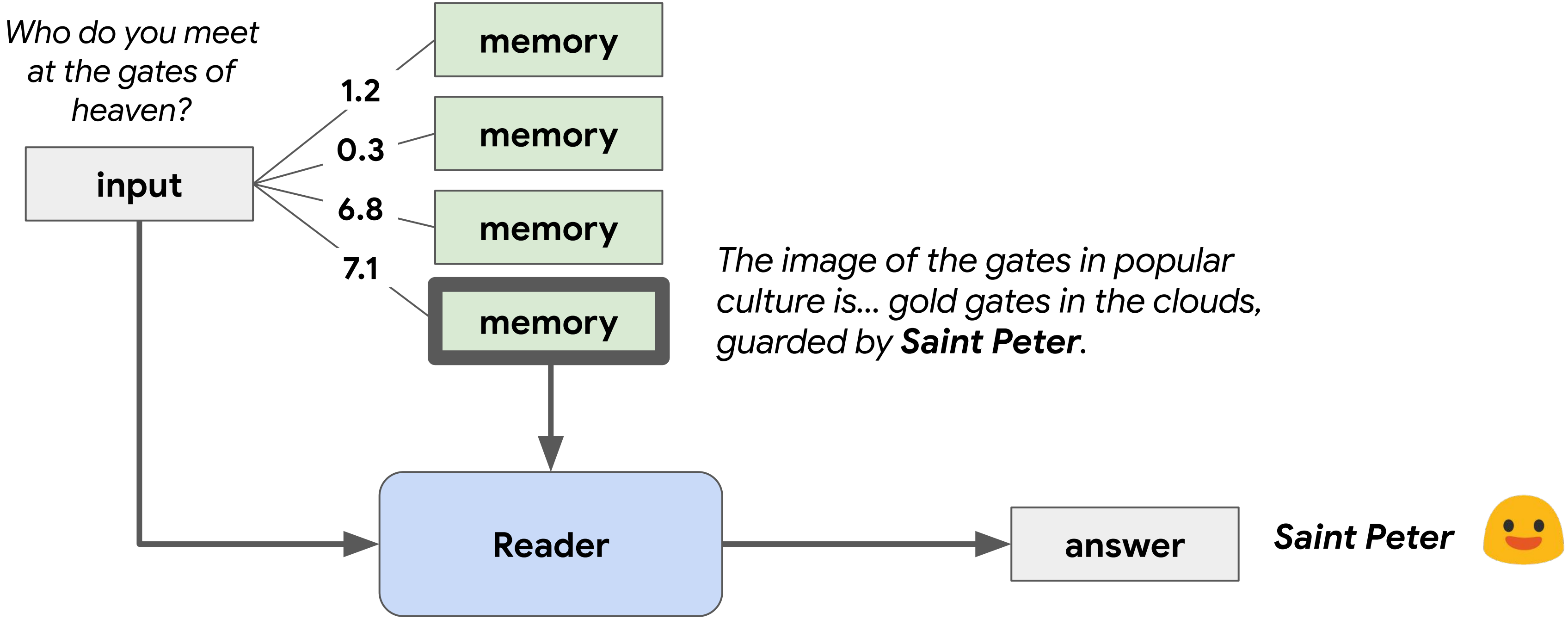
label smearing, aka **nearest neighbors**

Common failure modes

- **Underutilization:** model ignores retrieved memories.
- **Overreliance:** model depends too much on memories!

Underutilization of memories (Longpre et al, 2022)

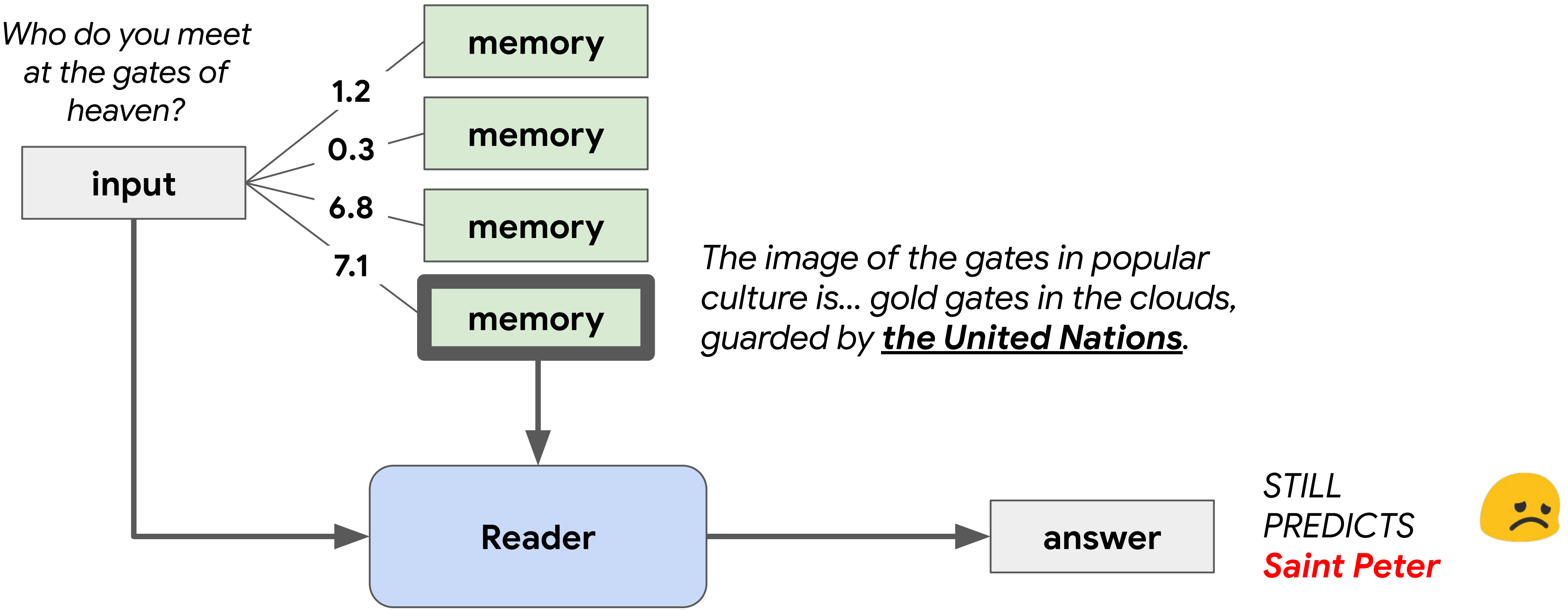
Underutilization of memories (Longpre et al, 2022)



The image of the gates in popular culture is... gold gates in the clouds, guarded by ***Saint Peter****.*

Saint Peter 😃

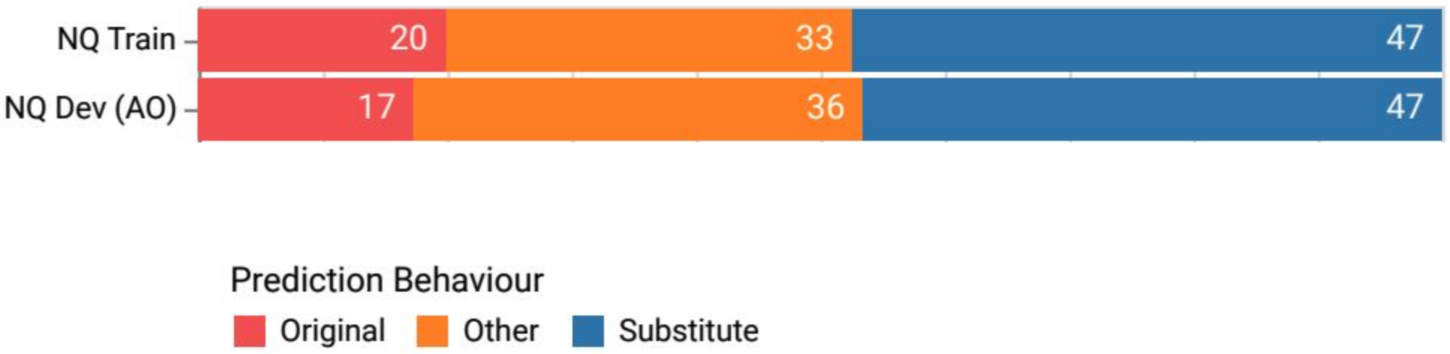
Underutilization of memories (Longpre et al, 2022)



The image of the gates in popular culture is… gold gates in the clouds, guarded by ***the United Nations****.*

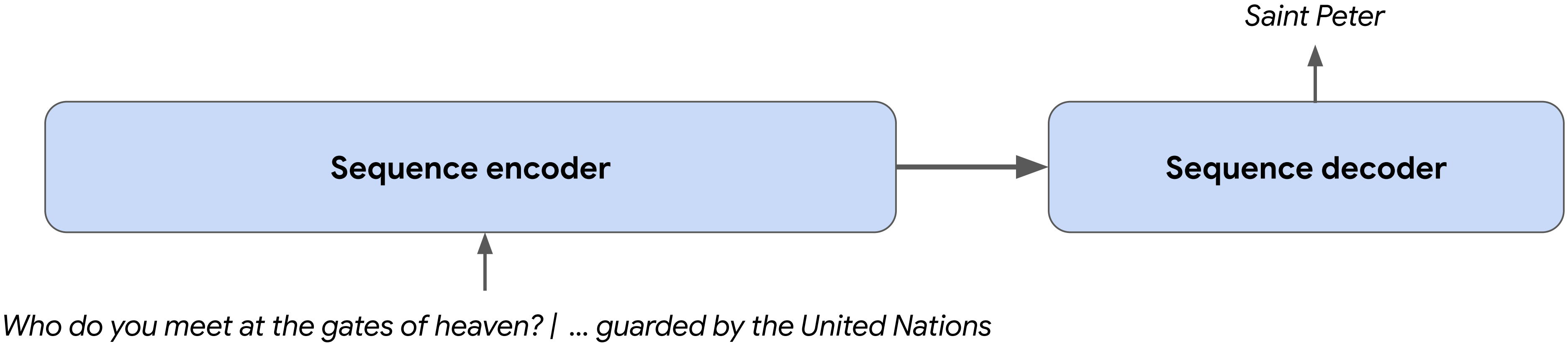
STILL PREDICTS ***Saint Peter*** 😟

How serious is this problem?



(This is evaluated on the subset of examples that the original model got right.)

Why is this happening?



Saint Peter

Sequence encoder

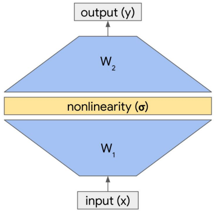
Sequence decoder

Who do you meet at the gates of heaven? | ... guarded by the United Nations

The **encoder** and **decoder** are both powerful Transformers that have their own **parametric memory**.

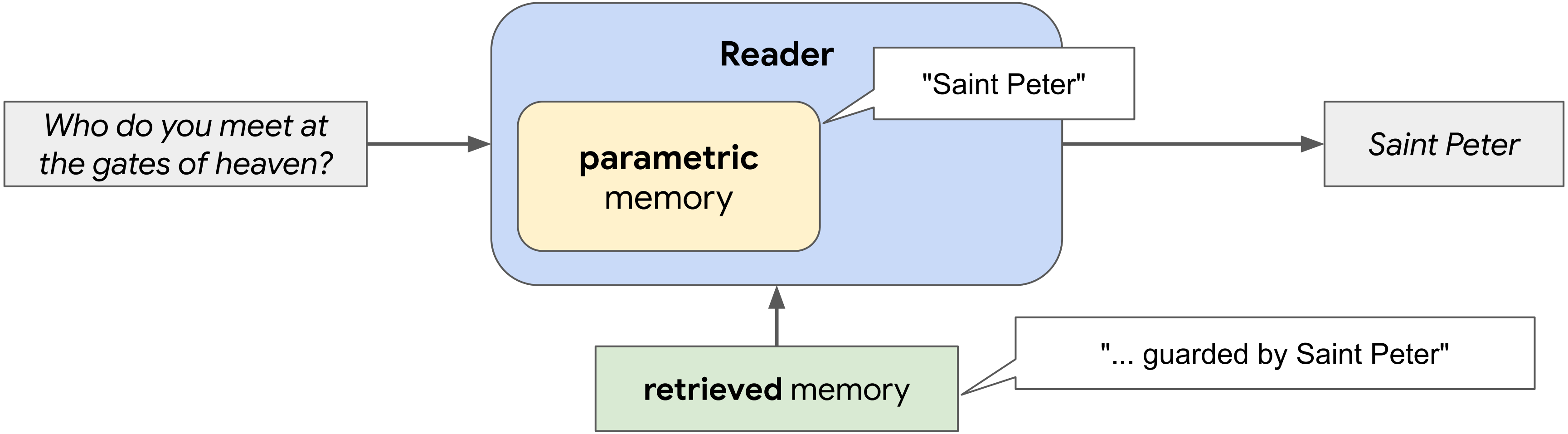
They learned to store the answer in their parametric memory, rather than learning to read the retrieved memory.

Transformer **feed-forward layers** are **key-value memories** (Geva et al, 2021)



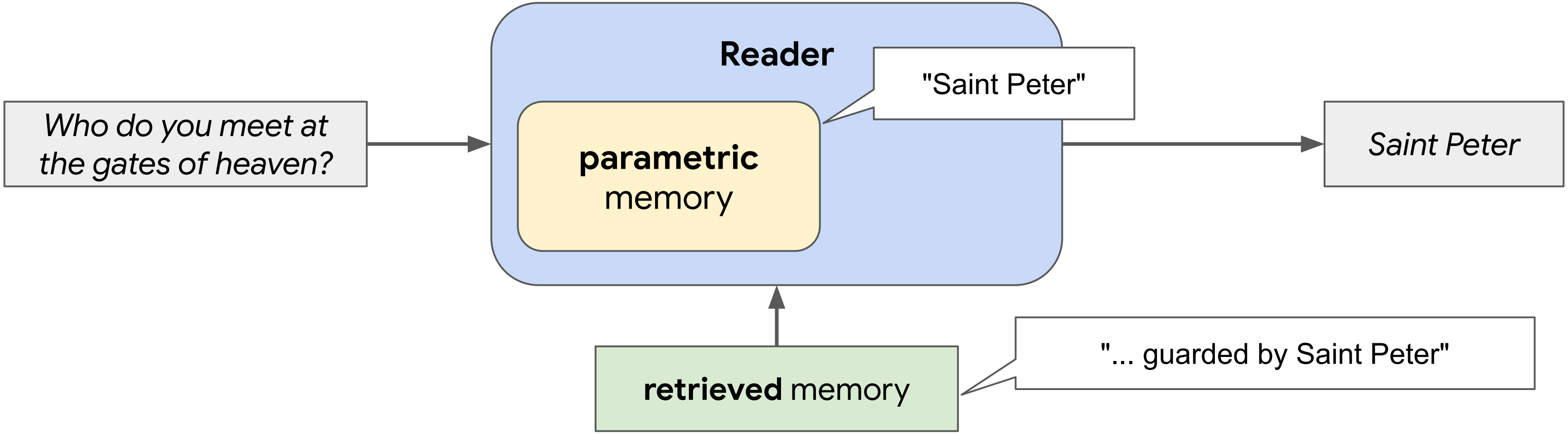
$$y = W_2\,\sigma(W_1 x + b)$$

How to fix this problem?



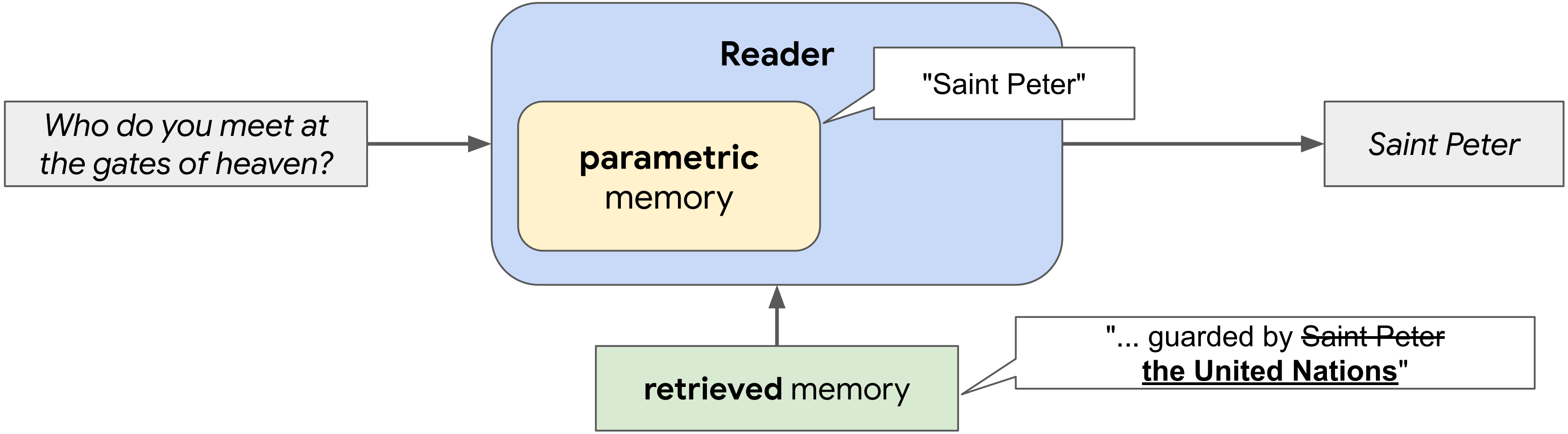
- We need to teach the Transformer that it should NOT rely on what it memorized in its feedforward layers.
- Instead, it should rely on what the external retrieved memory says.

How to fix this problem?



- In this case, **parametric** and **retrieved** are both right, so model can choose to use either one.
- We need examples where **parametric** is wrong, **retrieved** is right.

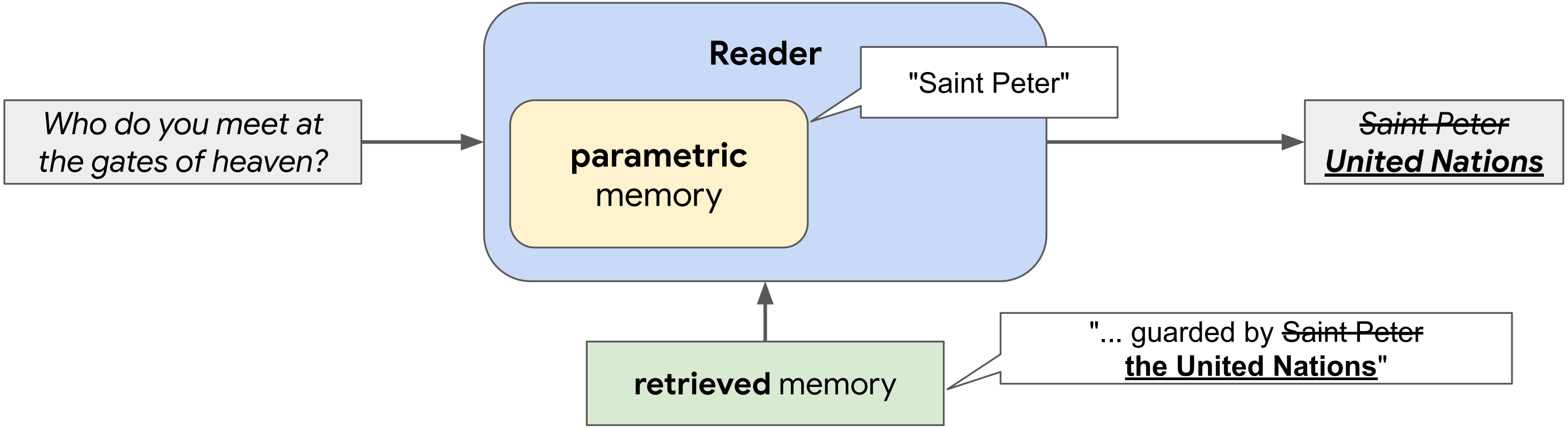
How to fix this problem?



Who do you meet at the gates of heaven?
Reader
"Saint Peter"
parametric memory
Saint Peter
retrieved memory
"... guarded by ~~Saint Peter~~ **the United Nations**"

- Modify the retrieved memory so that it no longer agrees with the parametric memory.

How to fix this problem?



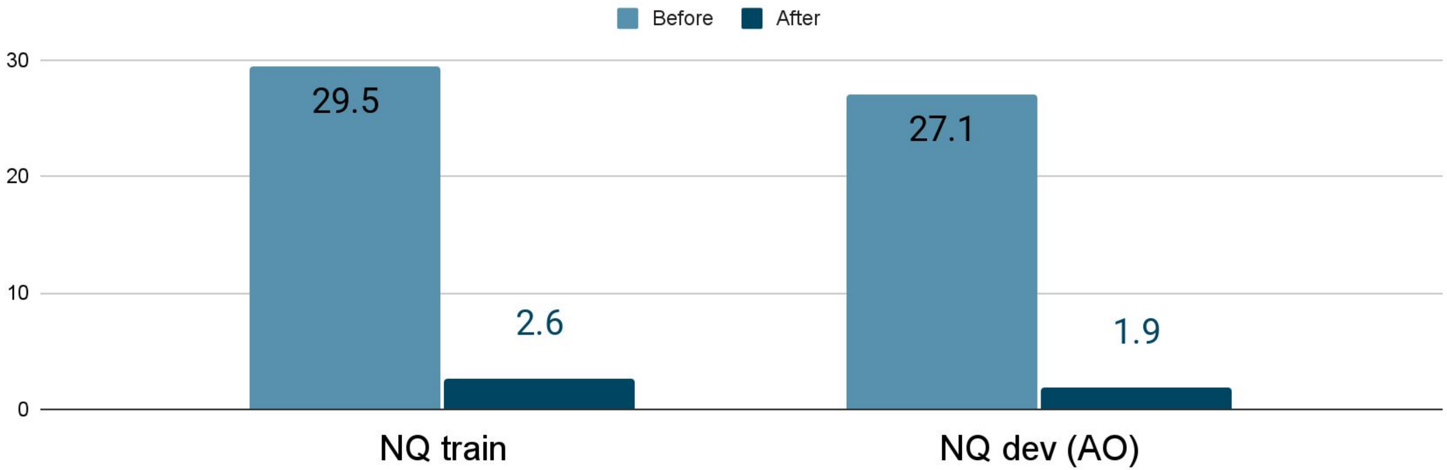
- Then, they change the ***gold answer*** to match the retrieved memory.
- Model learns that it cannot trust its parametric memory!
- "Data augmentation using **counterfactual memories**"

Does it work?

```
M = old / (old + new)
```

% of the time where model incorrectly reverts to original answer.

(ignoring cases where it produces neither old nor new answer)



Open challenges

- **Underutilization:** model ignores retrieved memories.
- **Overreliance:** model depends too much on memories!

Sometimes your memories are "too easy"

Query: "What year was the Eiffel Tower built?"
Answer: 1889

- **Typical memory:** "... work on the Eiffel Tower was completed in 1889."
  - Not too much word overlap.
  - Reader learns that "**completed**" means "**built**"
- **"Too easy" memory:** "The Eiffel Tower was built in the year 1889."
  - Heavy word overlap.
  - Model does not learn to paraphrase.
- **Challenging memory:** "Paris's tallest tower finished the same year Van Gogh painted The Starry Night".
  - Answer doesn't even directly appear -- requires inferences about other events.

If all your training memories are like this, Reader **never learns to handle paraphrase.**

Possible fix: at train time, filter out some % memories that have high lexical overlap.

If all your training memories are like this, Reader **can't figure it out, and may revert back to its parametric memory.**

Main takeaways

- Getting your model to use memory is not hard
  - **Text fusion:** Pass it as another text input
  - **Label smearing:** If each memory comes with a label, just copy the label
- But getting your model to **use memory correctly** is harder
  - **Underutilization:** if the model's **parametric memory** is strong, it may prefer that over your **external memory**.
  - **Overreliance:** if your memories are "too easy", it spoils the Reader: reader never learns to read deeply.

The end

This talk

- How do language models **currently** represent knowledge?
- What makes a good knowledge representation?
- How can we build better representations? → **Memory-augmented models**