

Interactive Fiction and Text Generation

Lara J. Martin (she/they)

<https://laramartin.net/interactive-fiction-class>

Learning Objectives

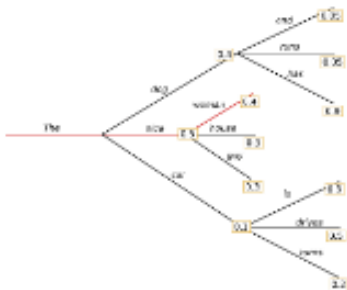
Understand the use & creation of dense vector embeddings

Calculate the distance between vector embeddings

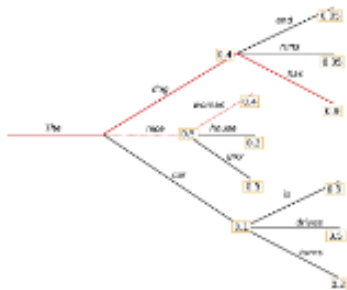
Recognize useful encoder-only, encoder-decoder, and decoder-only models

Differentiate between encoder model embeddings and older dense embeddings

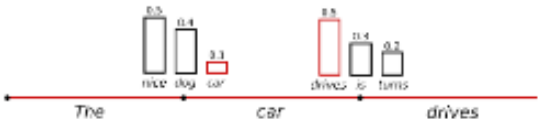
Review: Sampling



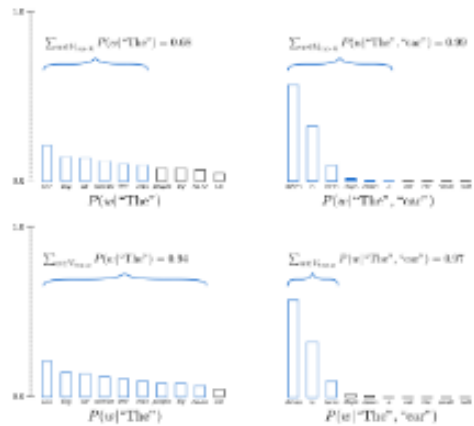
Greedy



Beam Search



Random Sampling



Top-K/P

Review

What's the difference between finetuning and prompting?

What's the difference between zero-shot and few-shot prompting?

Review: Tricks of the Trade

Instruction-tuned models like GPT-3.5 and Mistral-7B-Instruct like to be given a “role” first (e.g., “You are a helpful writing assistant.”)

The more defined the task, the better

- More details
- One thing to do at a time

LLMs are overly confident (like people on the internet)

- To “objectively” have the model evaluate something, you should have another instance judge

Chain-of-thought prompting helps models come up with better answers

They will “Yes and...” your prompt

LLM Vocabulary

Finetuning: Training an LLM more to adapt it to your task

Pre-training: The training before finetuning; creating a foundation model

Prompting: Getting the output you want by just changing the input; the model doesn't change

Zero-shot prompting: Prompting without examples

Few-shot prompting: Prompting with a few examples

Prompt engineering: Figuring out the right prompt for a task

Prompt tuning: Automated prompt engineering

Soft prompts: Computer-generated prompts

Hard prompts: Human-generated prompts

What might go wrong with finetuning?

Underfitting – finetuning data is too different from what the foundational model was trained on

Overfitting – overwrites what the model learned originally


Foundation Models

Types of Foundational Models

Encoder Only

Decoder Only

Encoder-Decoder Models



Denotes what they use during pre-training

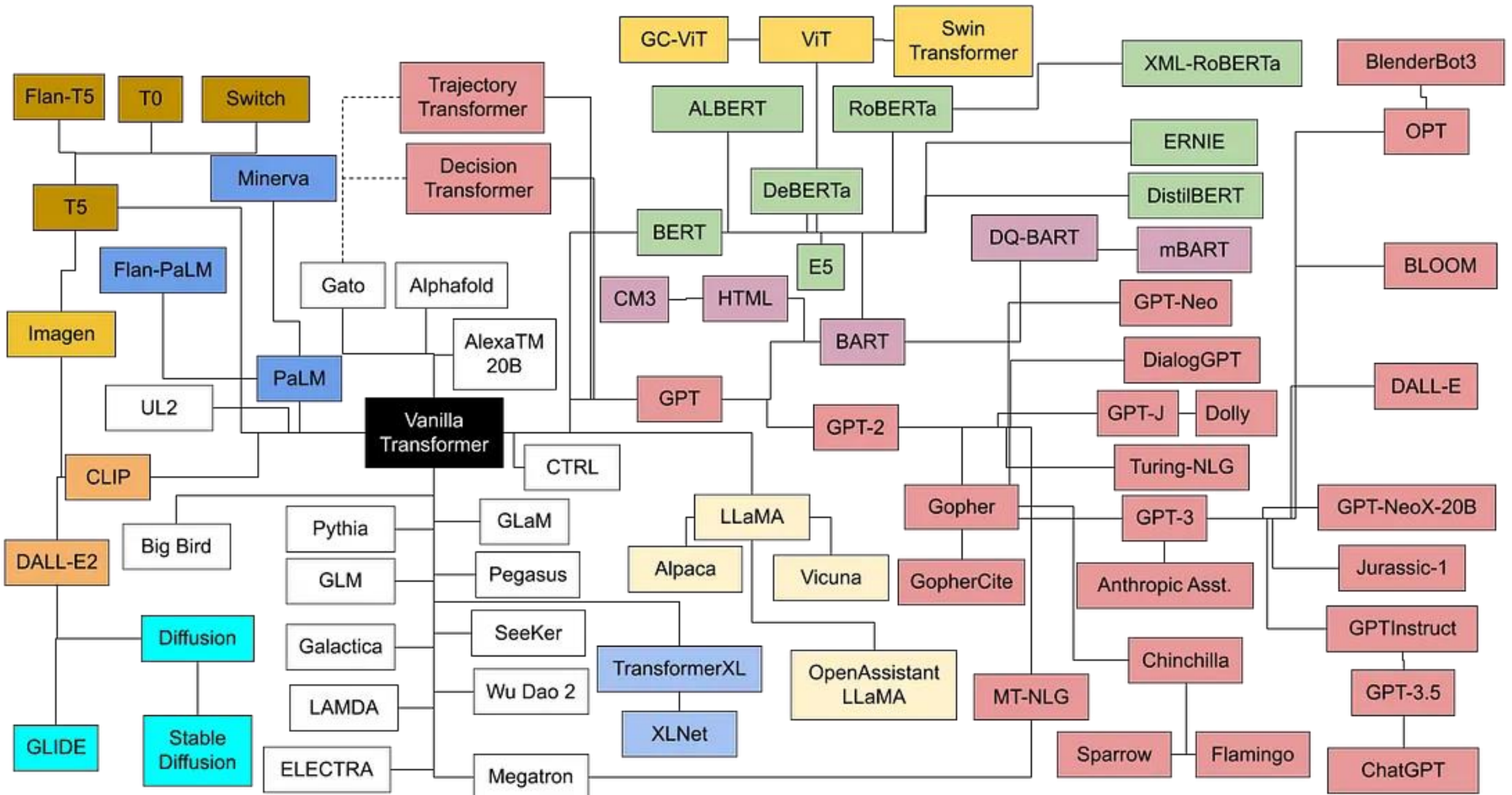
What is a foundational model?

A model that captures “foundational” or core information about a modality (e.g., text, speech, images)

Pretrained on a large amount of data & able to be finetuned on a particular task

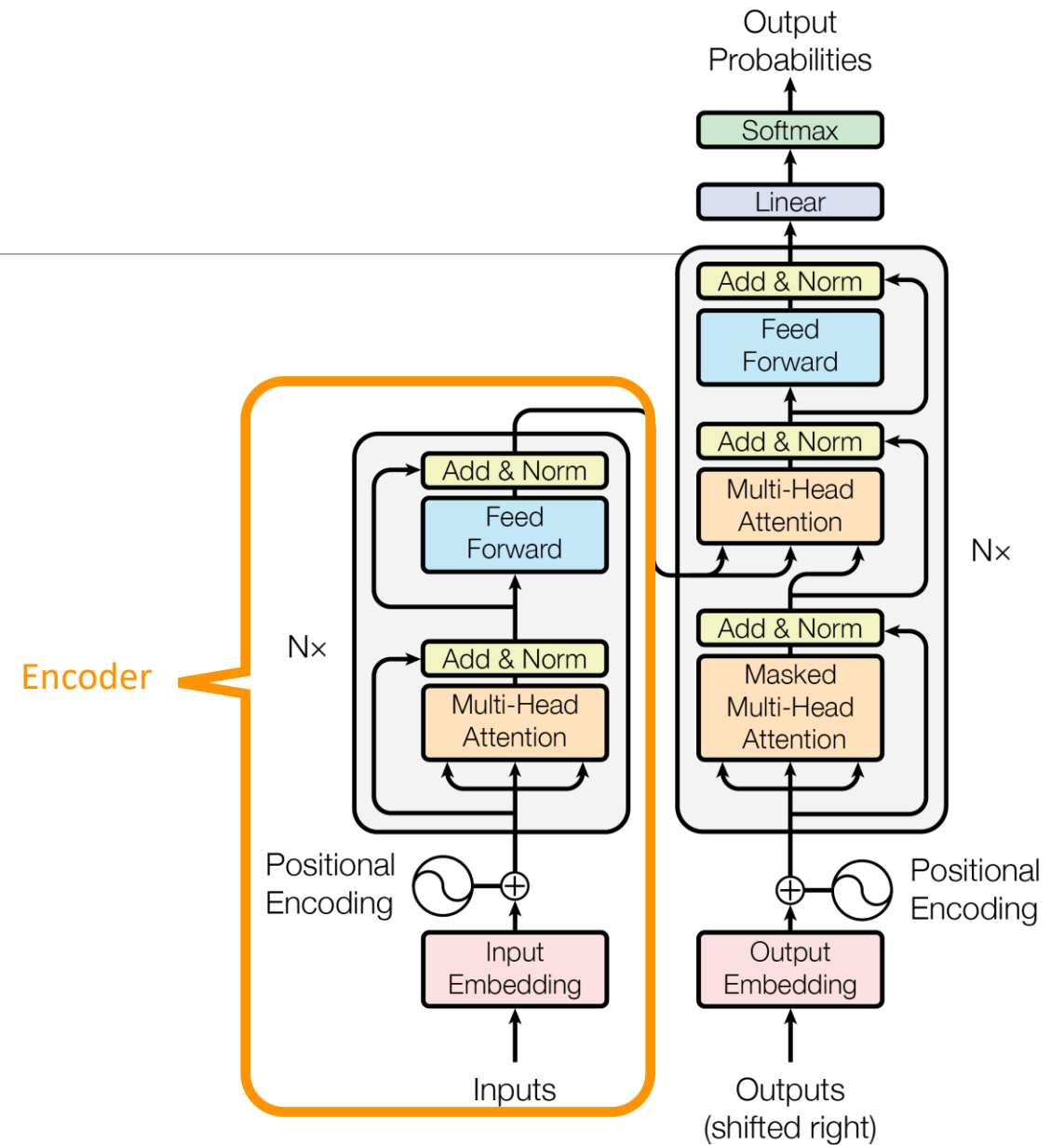
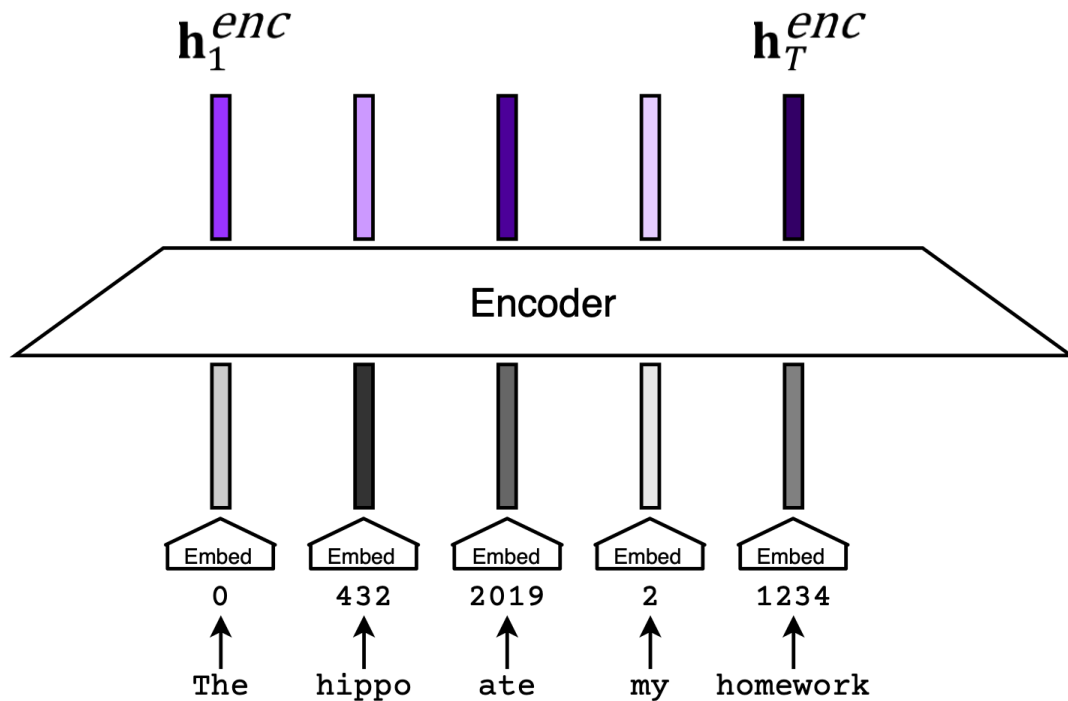
Self-supervised

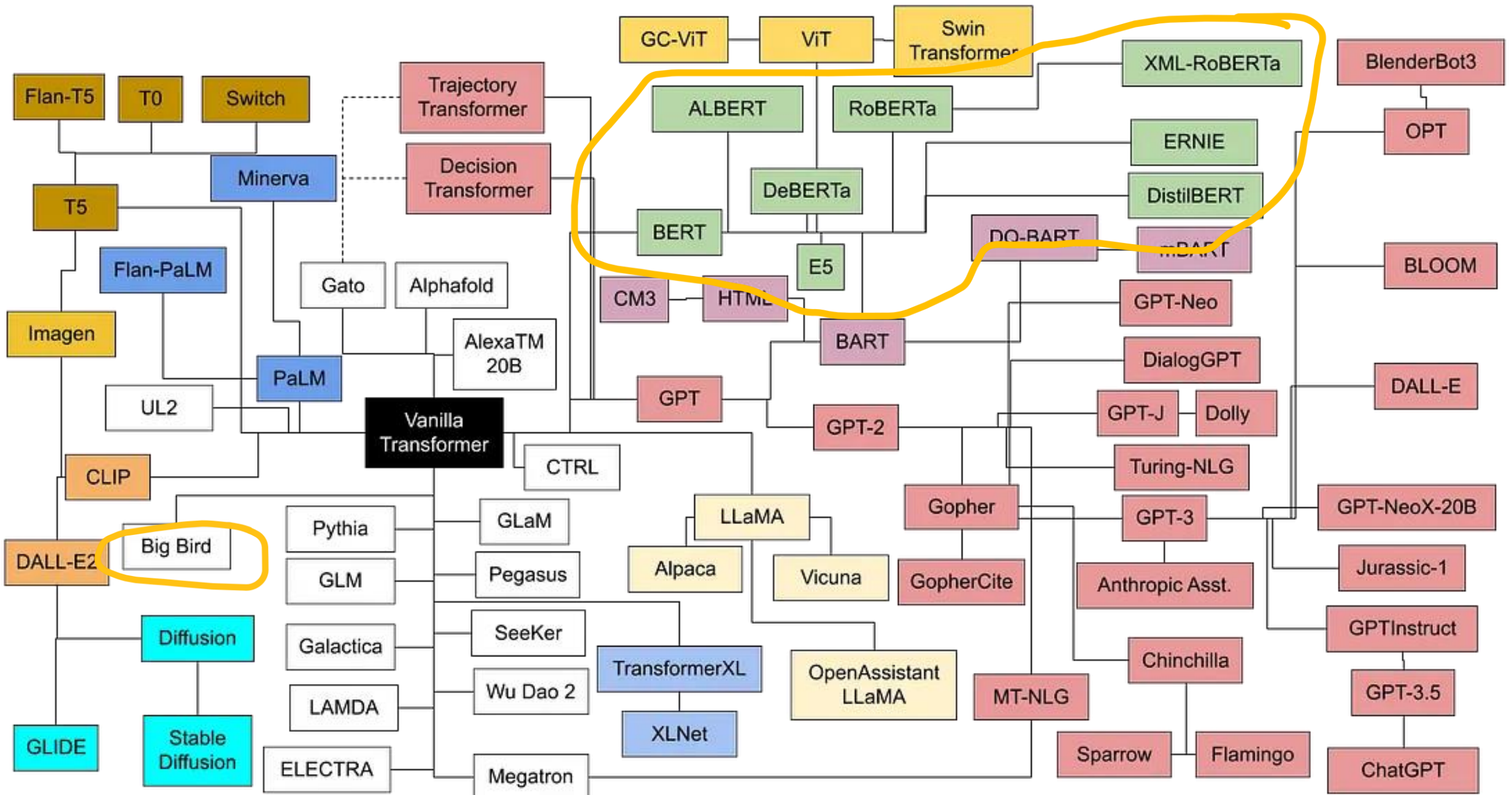
All non-finetuned large language models (LLMs) are foundational models



<https://amatriain.net/blog/transformer-models-an-introduction-and-catalog-2d1e9039f376/>

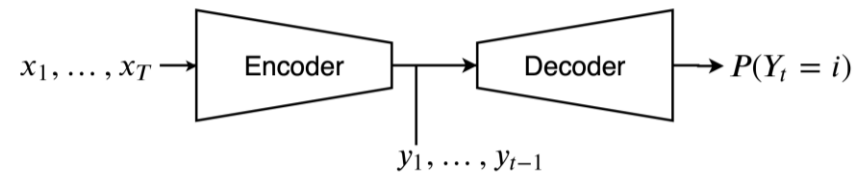
Encoder-only models





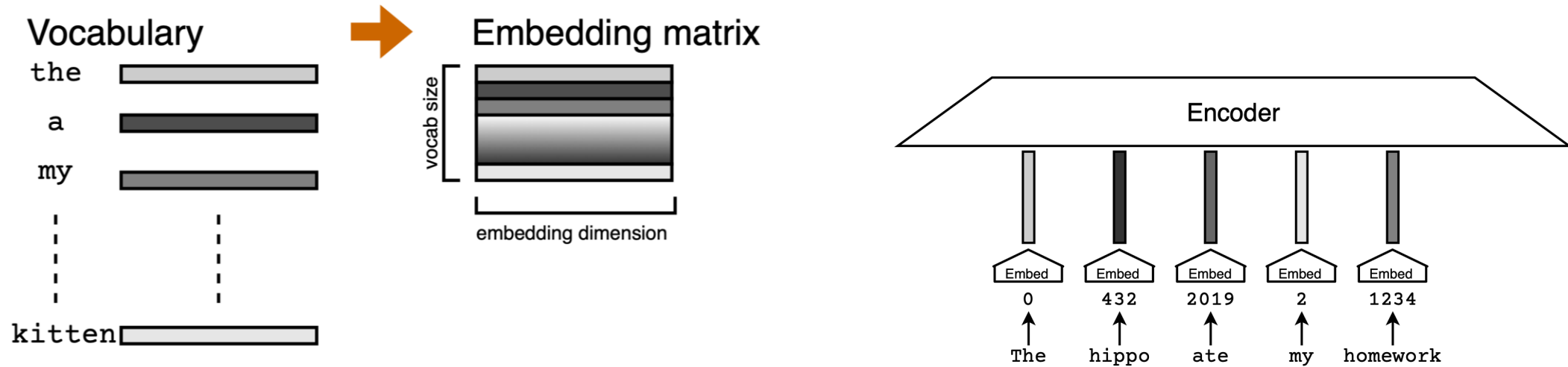
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Word Embeddings



Review: Inputs to the Encoder

The encoder takes as input the embeddings corresponding to each token in the sequence.



How have we represented words?

Each word is a distinct item

- Bijection between the strings and unique integer ids:
- "cat" --> 3, "kitten" --> 792 "dog" --> 17394

- Are "cat" and "kitten" similar?

Equivalently: "One-hot" encoding

- Represent each word type w with a vector the size of the vocabulary
- This vector has $V-1$ zero entries, and 1 non-zero (one) entry

One-Hot Encoding Example

Let our vocab be {a, cat, saw, mouse, happy}

$V = \# \text{ types} = 5$

Assign:

a	4
cat	2
saw	3
mouse	0
happy	1

How do we represent "cat?"

$$e_{\text{cat}} = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

How do we represent "happy?"

$$e_{\text{happy}} = \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

The Fragility of One-Hot Encodings

Case Study: Maxent Plagiarism Detector

Given two documents x_1, x_2 , predict $y = 1$ (plagiarized) or $y = 0$ (not plagiarized)

What is/are the:

Method/steps for predicting?

General formulation?

Features?



There's no way you'll
catch me!

Case Study: Maxent Plagiarism Detector (Feature Example)

Given two documents x_1, x_2 , predict $y = 1$ (plagiarized) or $y = 0$ (not plagiarized)

Intuition: documents are more likely to be plagiarized if they have words in common

$$f_{\text{any-common-word, Plag.}}(x_1, x_2) = ???$$

$$f_{\langle \text{word } v \rangle, \text{Plag.}}(x_1, x_2) = ???$$



Yes, but surely some words will be in common... these features won't catch phrases!

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Given two documents x_1, x_2 , predict $y = 1$ (plagiarized) or $y = 0$ (not plagiarized)

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n # adjacent words

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$$f_{\langle \text{ngram } Z \rangle, \text{Plag.}}(x_1, x_2) = ???$$

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No problem, I'll just change some words!

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$$f_{\text{synonym-of-}\langle \text{word } v \rangle, \text{Plag.}}(x_1, x_2) = ???$$



Okay... but there are too many possible synonym n-grams!

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A cartoon illustration of Mr. Burns from The Simpsons, depicted as a yellow-skinned man with a large nose, wearing a suit and tie. He is shown from the chest up, looking slightly to the right with a smug expression. A large orange speech bubble is positioned to his right, containing the text "Hah, I win!".

Hah, I win!

Plagiarism Detection: Word Similarity?

MAINFRAMES

Mainframes **are primarily** referred to large computers with **rapid**, advanced processing capabilities that **can execute and** perform tasks **equivalent to many** Personal Computers (PCs) machines **networked together**. It is **characterized with high quantity** Random Access Memory (RAM), very large secondary storage devices, and **high-speed** processors to cater for the needs of the computers under its service.

Consisting of advanced components, mainframes have the capability of running multiple large applications required by **many and** most enterprises **and organizations**. **This is** one of its advantages. Mainframes are also suitable to cater for those applications **(programs)** or files that are of very **high** demand by its users (clients). Examples of **such organizations and enterprises using mainframes are** online shopping websites **such as**

MAINFRAMES

Mainframes **usually are** referred those computers with **fast**, advanced processing capabilities that **could perform by itself** tasks **that may require a lot of** Personal Computers (PC) Machines. **Usually mainframes would have lots of** RAMs, very large secondary storage devices, and **very fast** processors to cater for the needs of those computers under its service.

Due to the advanced components mainframes have, **these computers** have the capability of running multiple large applications required by most enterprises, **which is** one of its advantage. Mainframes are also suitable to cater for those applications or files that are of very **large** demand by its users (clients). Examples of these **include** the large online shopping websites **-i.e. :** Ebay, Amazon, Microsoft, **etc.**

Word Embeddings

A dense, “low”-dimensional vector representation

Many values are not 0 (or at least less sparse than one-hot)

Up till ~2013: E could be any size
2013-present: E \ll vocab

An E-dimensional vector, often (but not always) real-valued

These are also called

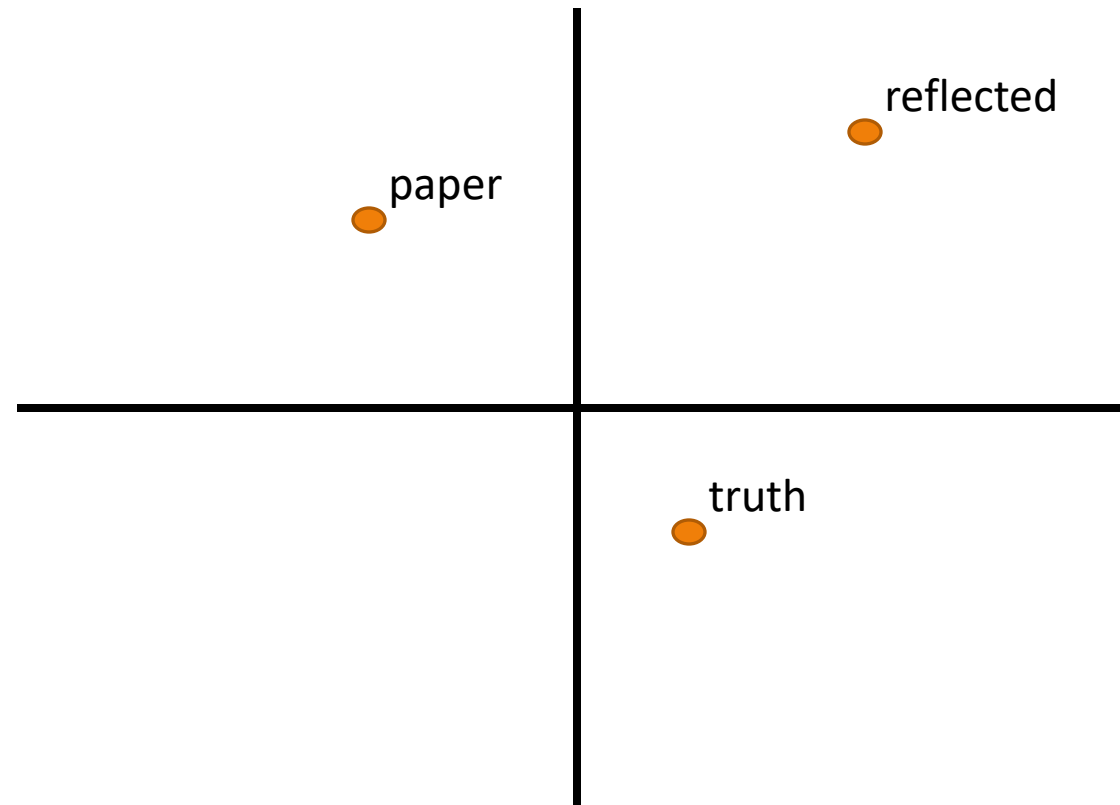
- **embeddings**
- **Continuous representations**
- **(word/sentence/...) vectors**
 - **Vector-space models**

Continuous Meaning

The paper reflected the truth.

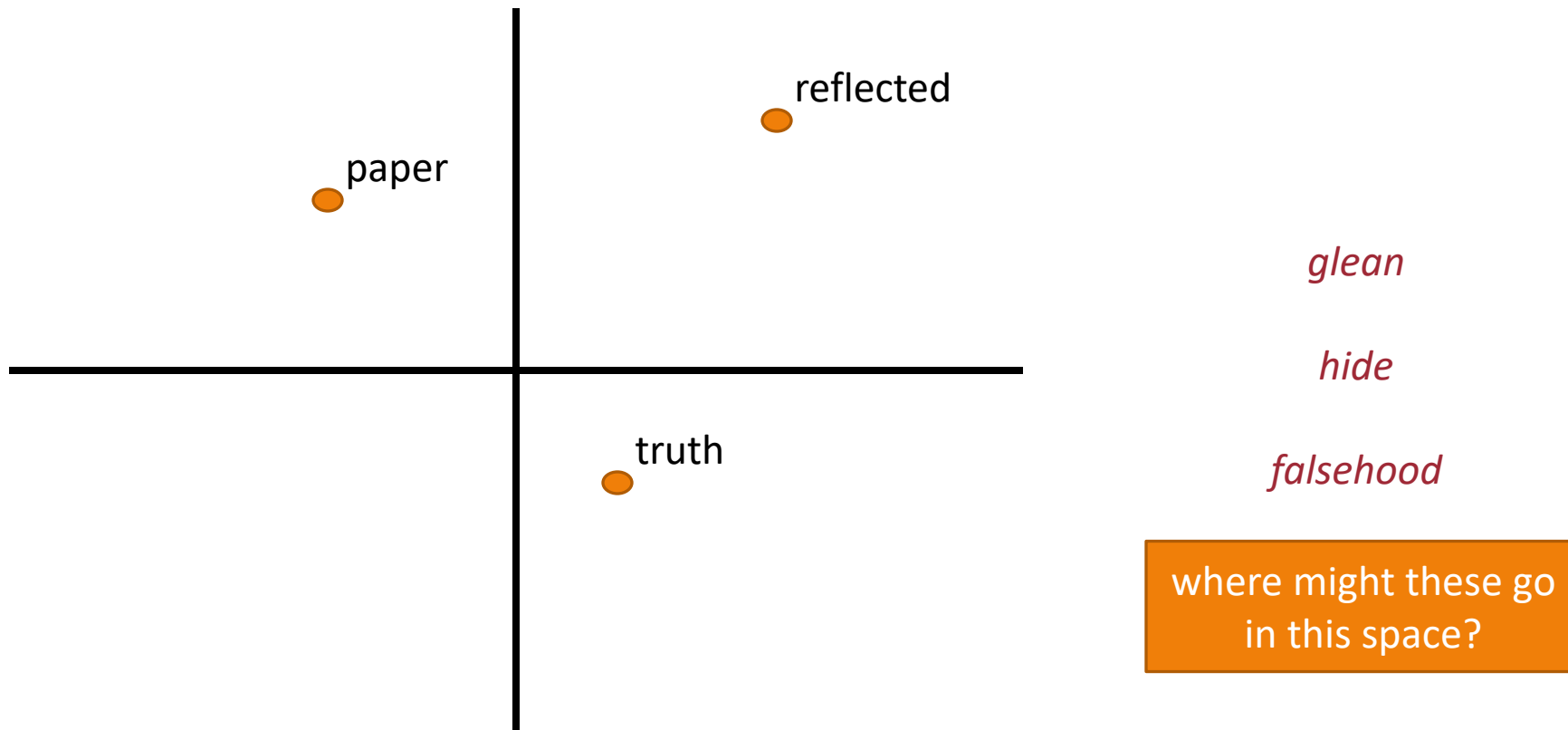
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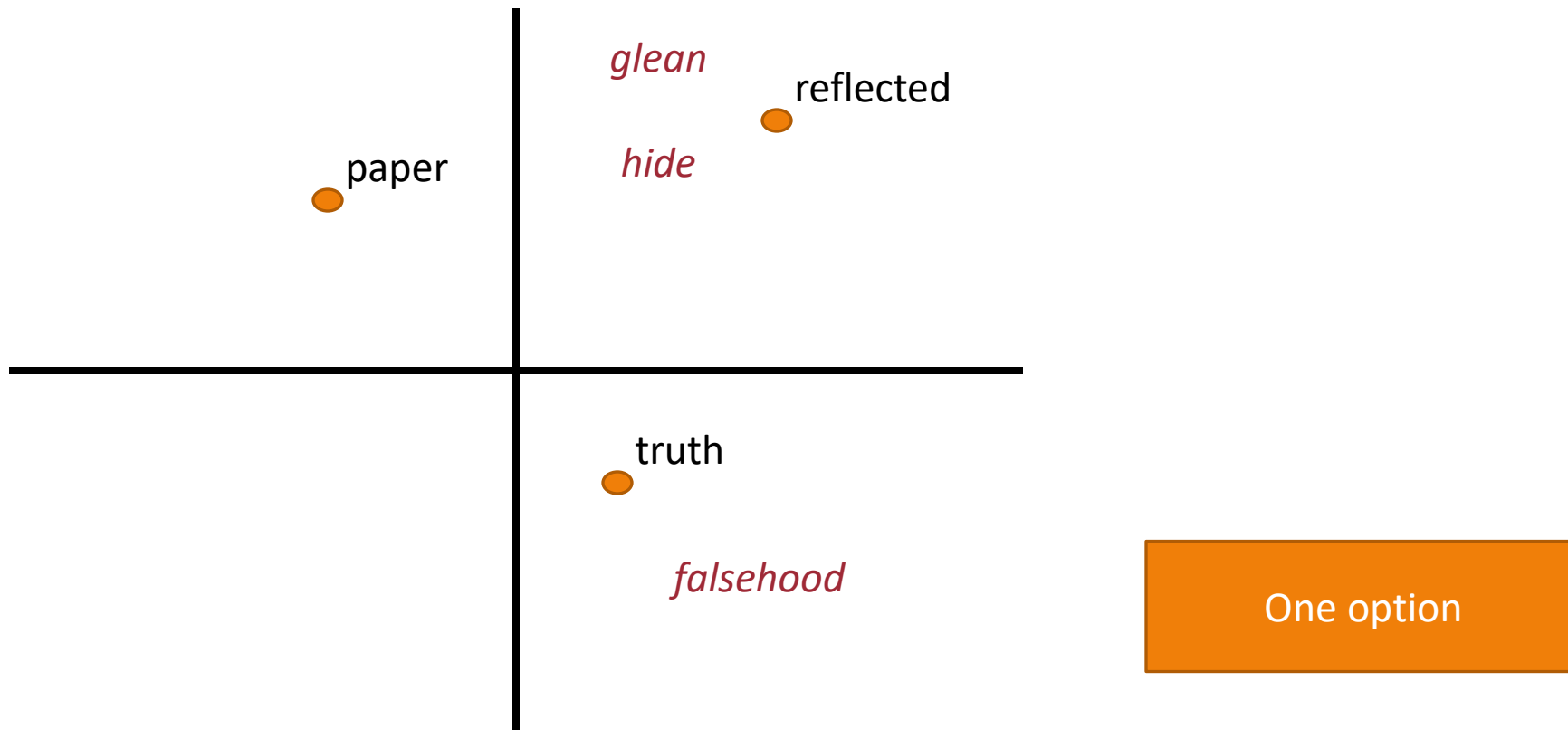
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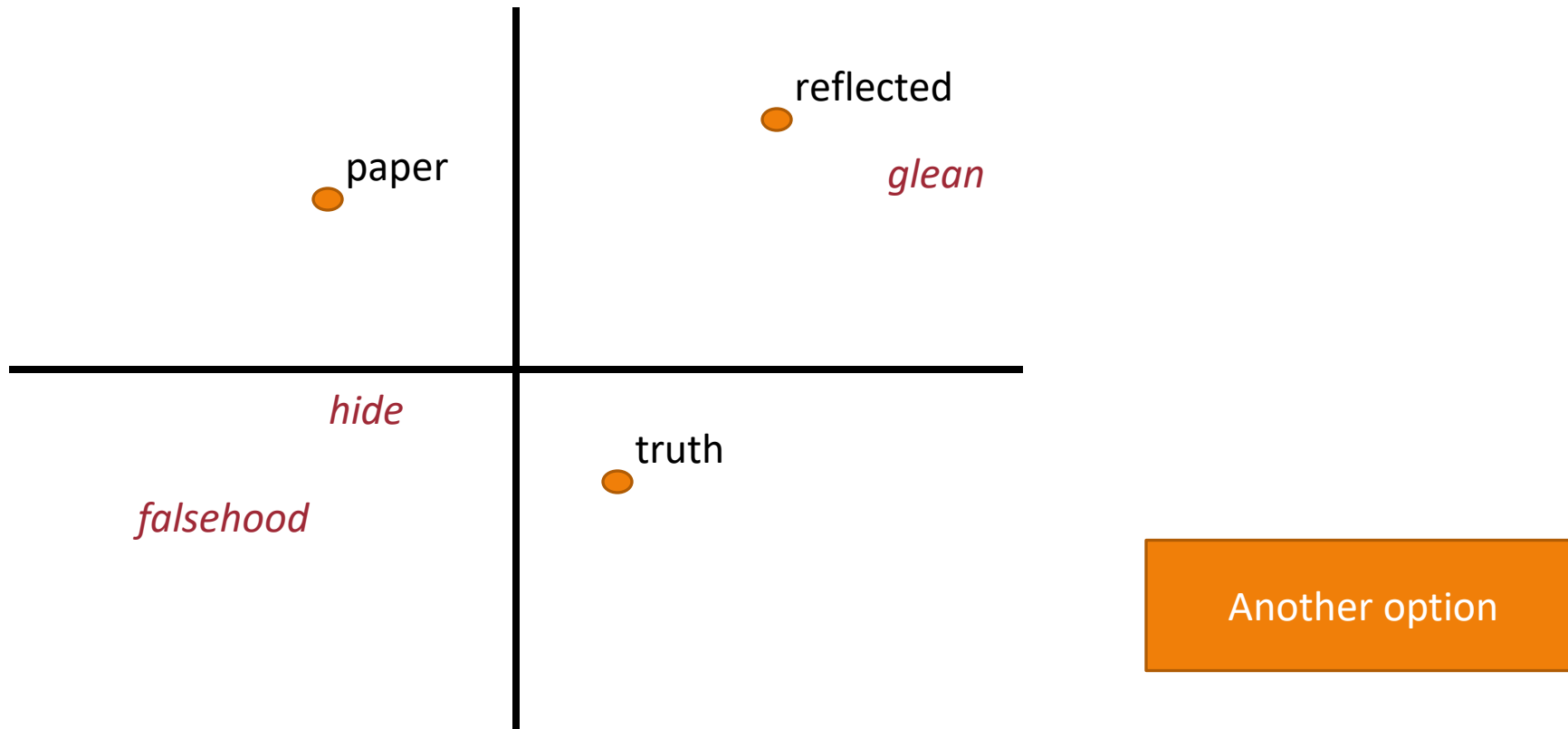
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(Some) Properties of Embeddings



https://media3.giphy.com/media/3orif0M8U1E7NfpFzq/200_s.gif

Capture “like” (similar) words

target:	Redmond	Havel	ninjutsu	graffiti	capitulate
	Redmond Wash.	Vaclav Havel	ninja	spray paint	capitulation
	Redmond Washington	president Vaclav Havel	martial arts	grafitti	capitulated
	Microsoft	Velvet Revolution	swordsmanship	taggers	capitulating

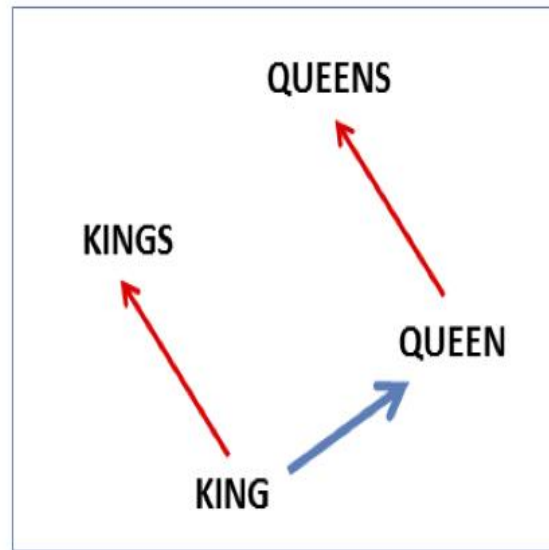
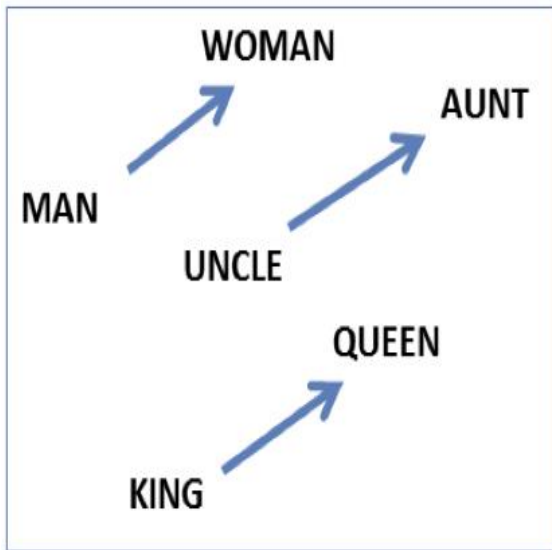
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	Redmond Washington	president Vaclav Havel	martial arts	grafitti	capitulated
	Microsoft	Velvet Revolution	swordsmanship	taggers	capitulating

Capture relationships



$$\text{vector}('king') - \text{vector}('man') + \text{vector}('woman') \approx \text{vector}('queen')$$

$$\text{vector}('Paris') - \text{vector}('France') + \text{vector}('Italy') \approx \text{vector}('Rome')$$

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`get_similarity_with_embeddings()`

Vector Representations

“Embeddings” Did Not Begin In This Century...

Hinton (1986): “Learning Distributed Representations of Concepts”

Deerwester et al. (1990): “Indexing by Latent Semantic Analysis”

Brown et al. (1992): “Class-based n-gram models of natural language”

Key Ideas

1. Acquire basic contextual statistics (often counts) for each word type v
2. Extract a real-valued vector e_v for each word v from those statistics
3. Use the vectors to represent each word in later tasks

Common Continuous Representations

Shared Intuition

Model the meaning of a word by “embedding” in a vector space

The meaning of a word is a vector of numbers

Contrast: word meaning is represented in many computational linguistic applications by a vocabulary index (“word number 545”) or the string itself

Three Common Kinds of Embedding Models

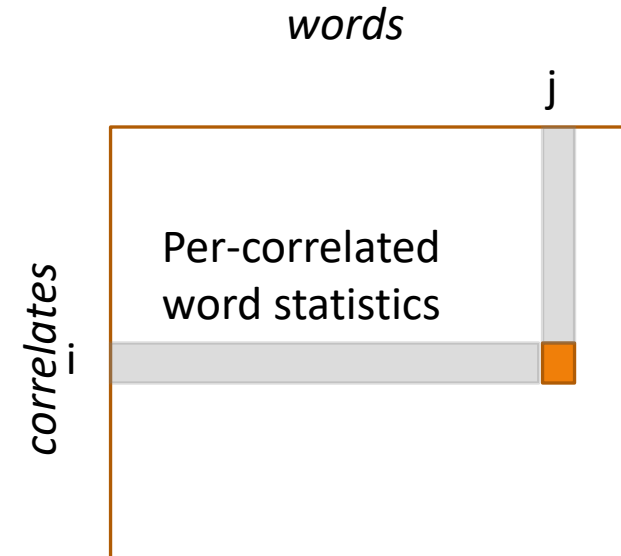
1. Co-occurrence matrices
- ~~2. Matrix Factorization: Singular value decomposition/Latent Semantic Analysis, Topic Models~~
3. Neural-network-inspired models (skip-grams, CBOW)

Three Common Kinds of Embedding Models

1. Co-occurrence matrices
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Co-occurrence Matrix

Acquire basic contextual statistics (often counts) for each word type v via *correlate*.



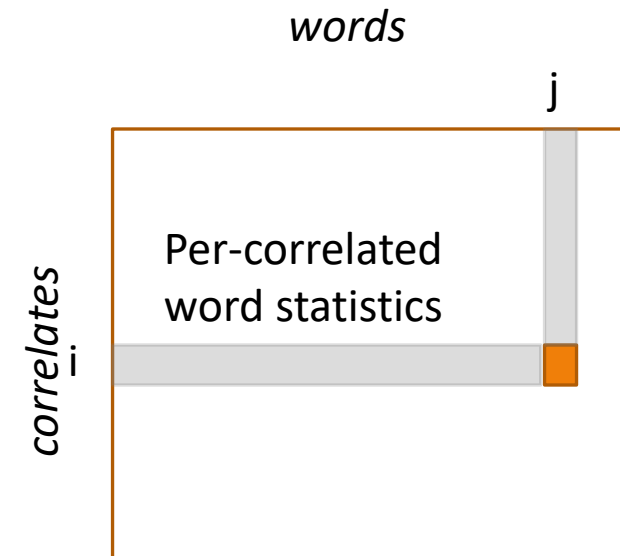
Co-occurrence Matrix

Acquire basic contextual statistics (often counts) for each word type v via *correlate*:

For example:

documents

- Record how often a word occurs in each document



correlates =
documents

Co-occurrence Matrix

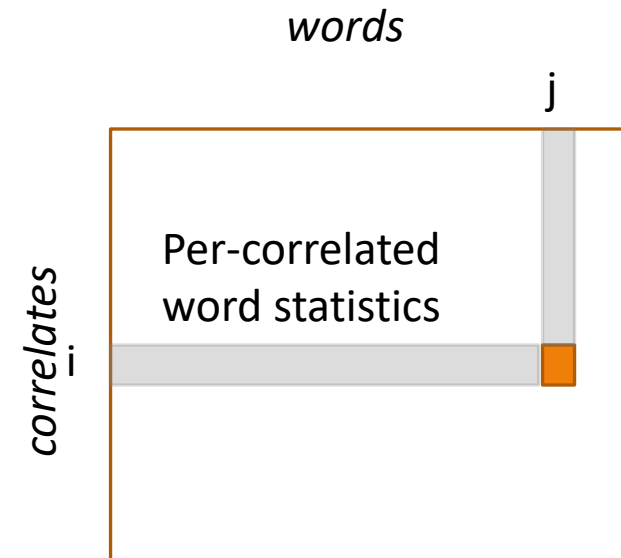
Acquire basic contextual statistics (often counts) for each word type v via *correlate*:

For example:

documents

surrounding context words

- Record how often v occurs with other word types u



correlates =
word types

Co-occurrence Matrix

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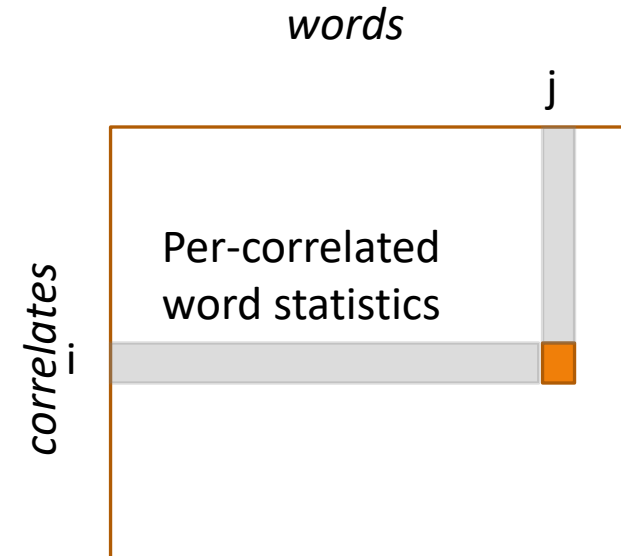
For example:

documents

surrounding context words

linguistic annotations (POS tags, syntax)

...



Assumption: Two words are similar if their vectors are similar

“Acquire basic contextual statistics (often counts) for each word type v ”

Two basic, initial counting approaches

- Record which words appear in which documents
- Record which words appear together

These are good first attempts, but with some large downsides

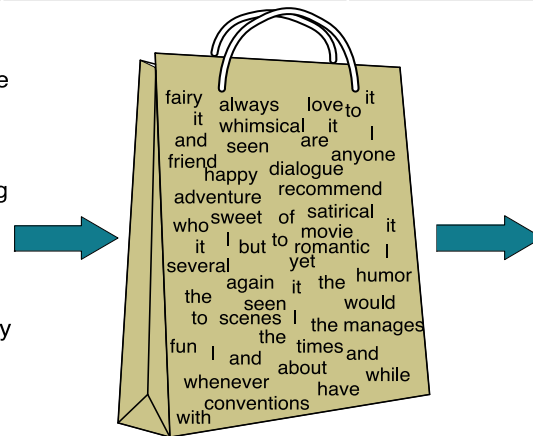
“You shall know a word by the company it keeps!” Firth (1957)

document (↓)-word (→) count matrix

	battle	soldier	fool	clown
<i>As You Like It</i>	1	2	37	6
<i>Twelfth Night</i>	1	2	58	117
<i>Julius Caesar</i>	8	12	1	0
<i>Henry V</i>	15	36	5	0

basic bag-of-words counting

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!



it 6
I 5
the 4
to 3
and 3
seen 2
yet 1
would 1
whimsical 1
times 1
sweet 1
satirical 1
adventure 1
genre 1
fairy 1
humor 1
have 1
great 1
... ..

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Assumption: Two words are similar if their vectors are similar

Issue: Count word vectors are very large, sparse, and skewed!

“You shall know a word by the company it keeps!” Firth (1957)

context (↓)-**word** (→) count matrix

	apricot	pineapple	digital	information
aardvark	0	0	0	0
computer	0	0	2	1
data	0	10	1	6
pinch	1	1	0	0
result	0	0	1	4
sugar	1	1	0	0

Context: those other words within a small “window” of a target word

“You shall know a word by the company it keeps!” Firth (1957)

context (↓)-word (→) count matrix

	apricot	pineapple	digital	information
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a cloud **computer** stores **digital data** on a remote computer

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Pointwise Mutual Information (PMI): Dealing with Problems of Raw Counts

Raw word frequency is not a great measure of association between words

It's very skewed: "the" and "of" are very frequent, but maybe not the most discriminative

We'd rather have a measure that asks whether a context word is **particularly informative** about the target word.

(Positive) Pointwise Mutual Information ((P)PMI)

Pointwise Mutual Information (PMI): Dealing with Problems of Raw Counts

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(Positive) Pointwise Mutual Information ((P)PMI)

Pointwise mutual information:

Do events x and y co-occur more than if they were independent?

probability words x and y occur together
(in the same context/window)

$$\text{PMI}(x, y) = \log \frac{p(x, y)}{p(x)p(y)}$$

probability that
word x occurs

probability that
word y occurs

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Word2Vec

Mikolov et al. (2013; NeurIPS): “Distributed Representations of Words and Phrases and their Compositionality”

Revisits the context-word approach

Learn a model $p(c | w)$ to predict a context word from a target word

Word2Vec

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Revisits the context-word approach

Learn a model $p(c | w)$ to predict a context word from a target word

Learn two types of vector representations

- $h_c \in \mathbb{R}^E$: vector embeddings for each context word
- $v_w \in \mathbb{R}^E$: vector embeddings for each target word

$$p(c | w) \propto \exp(h_c^T v_w)$$

Word2Vec

context (↓)-**word** (→) count matrix

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Context: those other words within a small “window” of a target word

$$\max_{h,v} \sum_{c,w \text{ pairs}} \text{count}(c, w) \log p(c | w)$$

$$p(c | w) \propto \exp(h_c^T v_w)$$

Word2Vec has Inspired a Lot of Work

Off-the-shelf embeddings

- <https://code.google.com/archive/p/word2vec/>

Off-the-shelf implementations

- <https://radimrehurek.com/gensim/models/word2vec.html>

Follow-on work

- “GloVe: Global Vectors for Word Representation” (Pennington, Socher and Manning, 2014)
 - <https://nlp.stanford.edu/projects/glove/>
- Many others
- 15000+ citations

Comparing/Evaluating Word Embeddings

Common Evaluation: Correlation between similarity ratings

Input: list of N word pairs $\{(x_1, y_1), \dots, (x_N, y_N)\}$

- Each word pair (x_i, y_i) has a human-provided similarity score h_i

Use your embeddings to compute an embedding similarity score $s_i = \text{sim}(x_i, y_i)$

Compute the correlation between human and computed similarities

$$\rho = \text{Corr}((h_1, \dots, h_N), (s_1, \dots, s_N))$$

Wordsim353: 353 noun pairs rated 0-10

Cosine: Measuring Similarity

Given 2 target words v and w how similar are their vectors?

Dot product or inner product from linear algebra

$$\text{dot-product}(\vec{v}, \vec{w}) = \vec{v} \cdot \vec{w} = \sum_{i=1}^N v_i w_i = v_1 w_1 + v_2 w_2 + \dots + v_N w_N$$

- High when two vectors have large values in same dimensions, low for orthogonal vectors with zeros in complementary distribution

Correct for high magnitude vectors

$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}| |\vec{b}|}$$

Cosine Similarity

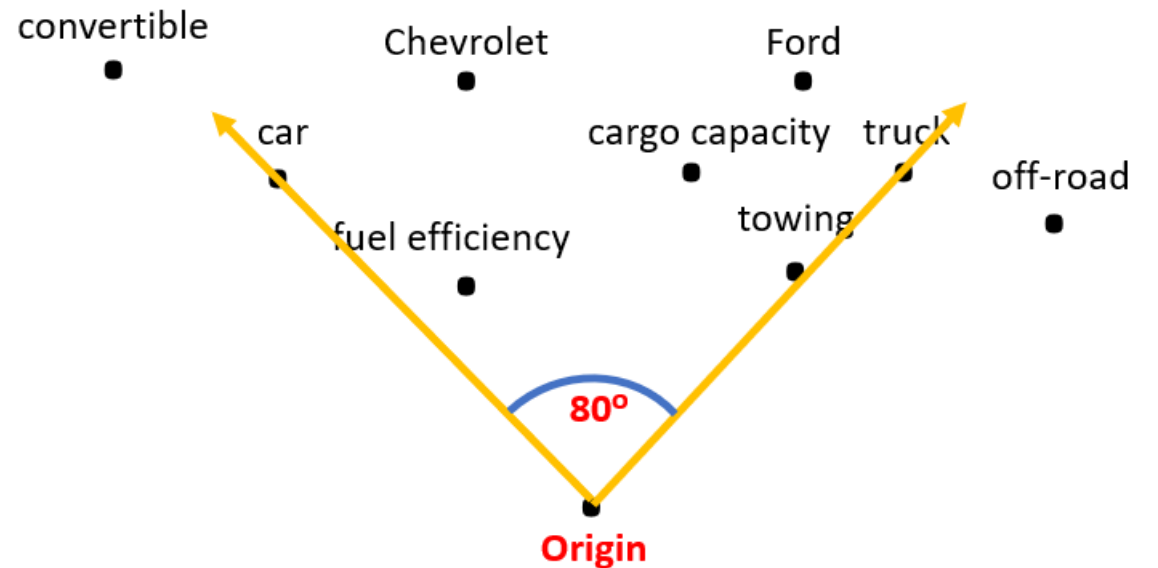
Divide the dot product by the length of the two vectors

$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}| |\vec{b}|}$$

This is the cosine of the angle between them

$$\vec{a} \cdot \vec{b} = |\vec{a}| |\vec{b}| \cos \theta$$

$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}| |\vec{b}|} = \cos \theta$$



<https://upload.wikimedia.org/wikipedia/commons/2/23/CosineSimilarity.png>

Example: Word Similarity

$$\cos(x, y) = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2} \sqrt{\sum_i y_i^2}}$$

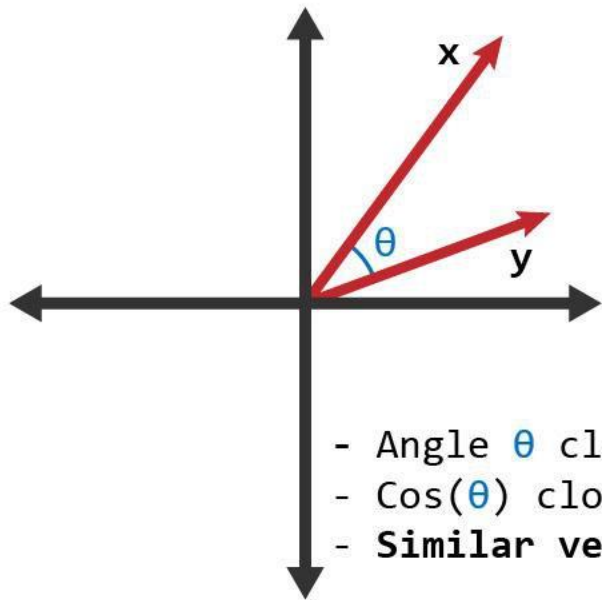
	Dim. 1	Dim. 2	Dim. 3
apricot	2	0	0
digital	0	1	2
information	1	6	1

$$\text{cosine}(\text{apricot}, \text{information}) = \frac{2 + 0 + 0}{\sqrt{4 + 0 + 0} \sqrt{1 + 36 + 1}} = 0.1622$$

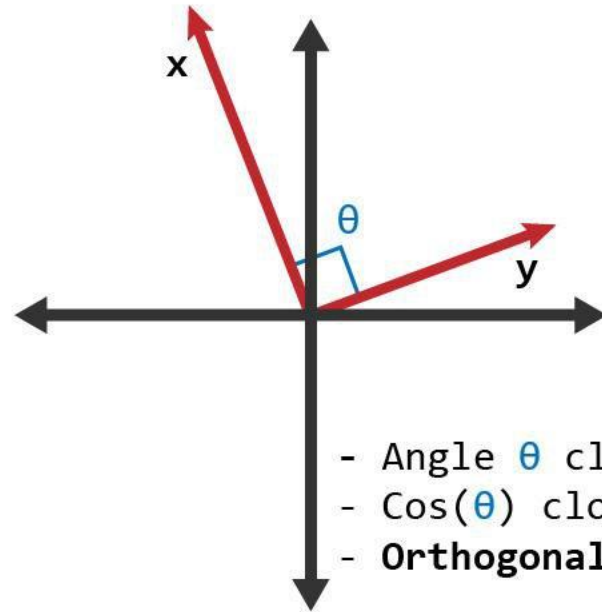
$$\text{cosine}(\text{digital}, \text{information}) = \frac{0 + 6 + 2}{\sqrt{0 + 1 + 4} \sqrt{1 + 36 + 1}} = 0.5804$$

$$\text{cosine}(\text{apricot}, \text{digital}) = \frac{0 + 0 + 0}{\sqrt{4 + 0 + 0} \sqrt{0 + 1 + 4}} = 0.0$$

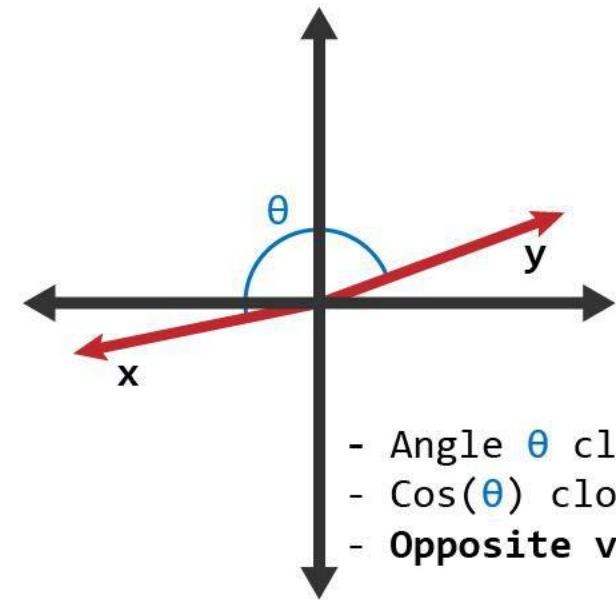
Cosine Similarity Range



- Angle θ close to 0
- $\text{Cos}(\theta)$ close to 1
- **Similar vectors**



- Angle θ close to 90
- $\text{Cos}(\theta)$ close to 0
- **Orthogonal vectors**



- Angle θ close to 180
- $\text{Cos}(\theta)$ close to -1
- **Opposite vectors**

<https://www.learnatasci.com/glossary/cosine-similarity/>

Other Similarity Measures

$$\text{sim}_{\text{cosine}}(\vec{v}, \vec{w}) = \frac{\vec{v} \cdot \vec{w}}{|\vec{v}| |\vec{w}|} = \frac{\sum_{i=1}^N v_i \times w_i}{\sqrt{\sum_{i=1}^N v_i^2} \sqrt{\sum_{i=1}^N w_i^2}}$$

$$\text{sim}_{\text{Jaccard}}(\vec{v}, \vec{w}) = \frac{\sum_{i=1}^N \min(v_i, w_i)}{\sum_{i=1}^N \max(v_i, w_i)}$$

$$\text{sim}_{\text{Dice}}(\vec{v}, \vec{w}) = \frac{2 \times \sum_{i=1}^N \min(v_i, w_i)}{\sum_{i=1}^N (v_i + w_i)}$$

$$\text{sim}_{\text{JS}}(\vec{v} || \vec{w}) = D\left(\vec{v} \middle| \frac{\vec{v} + \vec{w}}{2}\right) + D\left(\vec{w} \middle| \frac{\vec{v} + \vec{w}}{2}\right)$$

Other Neural Word Embedding Models

FastText

“Enriching Word Vectors with Subword Information” Bojanowski et al. (2017; TACL)

Main idea: learn **character n-gram embeddings** for the target word (not context) and modify the word2vec model to use these

Pre-trained models in 150+ languages

- <https://fasttext.cc>

FastText Details

Main idea: learn **character n-gram embeddings** and for the target word (not the context) modify the word2vec model to use these

Original word2vec:

$$p(c | w) \propto \exp(h_c^T v_w)$$

FastText:

$$p(c | w) \propto \exp\left(h_c^T \left(\sum_{\text{n-gram } g \text{ in } w} z_g\right)\right)$$

FastText Details

Main idea: learn **character n-gram embeddings** and for the target word (not the context) modify the word2vec model to use these

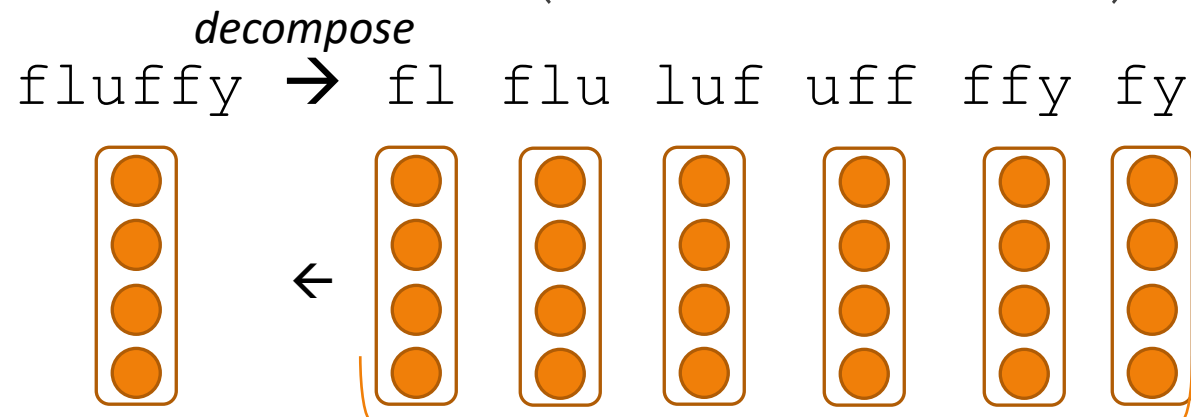
$$p(c | w) \propto \exp \left(h_c^T \left(\sum_{\text{n-gram } g \text{ in } w} z_g \right) \right)$$

decompose
fluffy \rightarrow fl flu luf uff ffy fy

FastText Details

Main idea: learn **character n-gram embeddings** and for the target word (not the context) modify the word2vec model to use these

$$p(c | w) \propto \exp \left(h_c^T \left(\sum_{\text{n-gram } g \text{ in } w} z_g \right) \right)$$



*To deterministically
compute word embeddings*

*Learn n-gram
embeddings*



Contextual Word Embeddings

Word2vec-based models are not context-dependent

Single word type → single word embedding

If a single word type can have different meanings...

bank, bass, plant,...

... why should we only have one embedding?

Entire task devoted to classifying these meanings:

Word Sense Disambiguation

Contextual Word Embeddings

Growing interest in this

Off-the-shelf is a bit more difficult

- Download and run a model
- Can't just download a file of embeddings

Two to know about (with code):

- ELMo: “Deep contextualized word representations” Peters et al. (2018; NAACL)
- <https://allennlp.org/elmo>
- BERT: “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding” Devlin et al. (2019; NAACL)
- <https://github.com/google-research/bert>



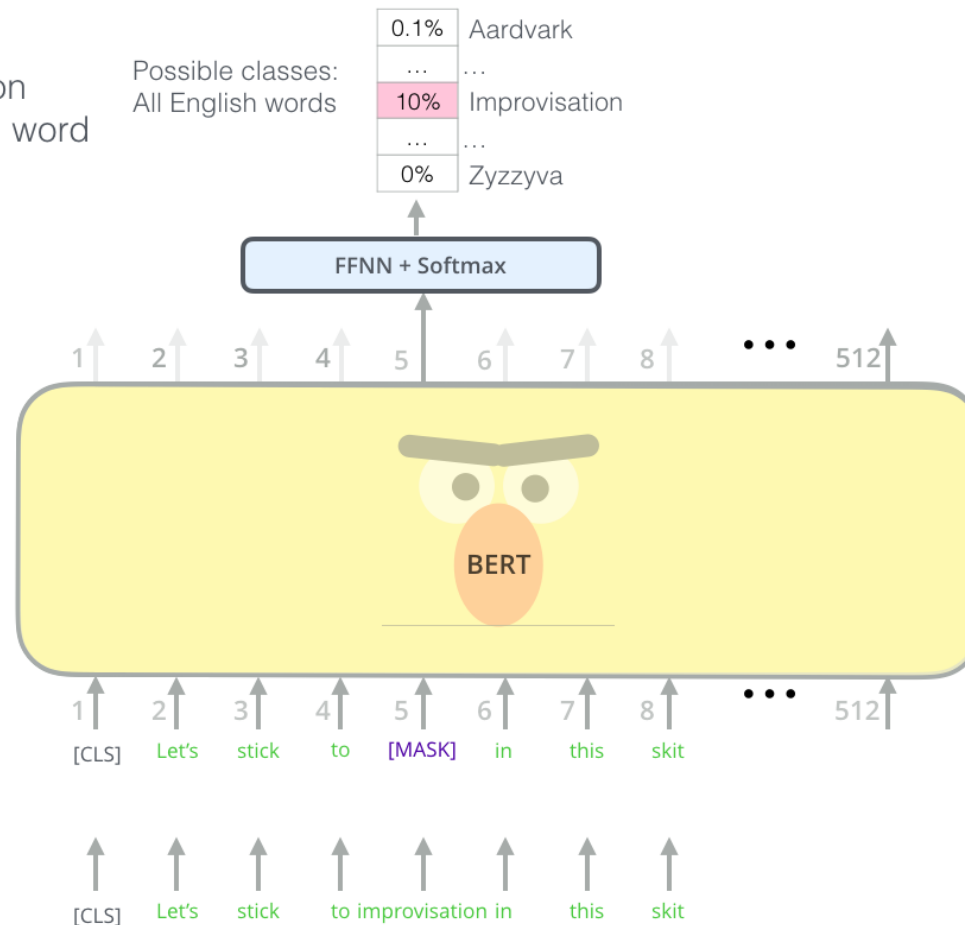
Back to Transformers...

BERT (Devlin et al. 2019)

Use the output of the masked word's position to predict the masked word

Randomly mask 15% of tokens

Input



Possible classes:
All English words

FFNN + Softmax

BERT

[CLS] Let's stick to [MASK] in this skit

[CLS] Let's stick to improvisation in this skit

Uses of Encoder-Only Models

Classification tasks

Sentence embeddings

Context-dependent word embeddings

Any type of fill-in-the-blank tasks

BERT Question

Consider the highlighted words. Which two words would contextual word embeddings from BERT say are closest?

- A. I am so excited to use my new bat at the baseball game tomorrow.
- B. The favorite food of this species of bat is mosquitoes.
- C. The cardinal isn't just a lawn decoration; the species makes themselves useful by eating mosquitoes.

PollEv.com/laramartin527



Remember: word2vec is a dense vector embedding

Word2Vec Question

Consider the highlighted words. Which two words would word2vec say are closest?

- A. I am so excited to use my new bat at the baseball game tomorrow.
- B. The favorite food of this species of bat is mosquitoes.
- C. The cardinal isn't just a lawn decoration; the species makes themselves useful by eating mosquitoes.

PollEv.com/laramartin527



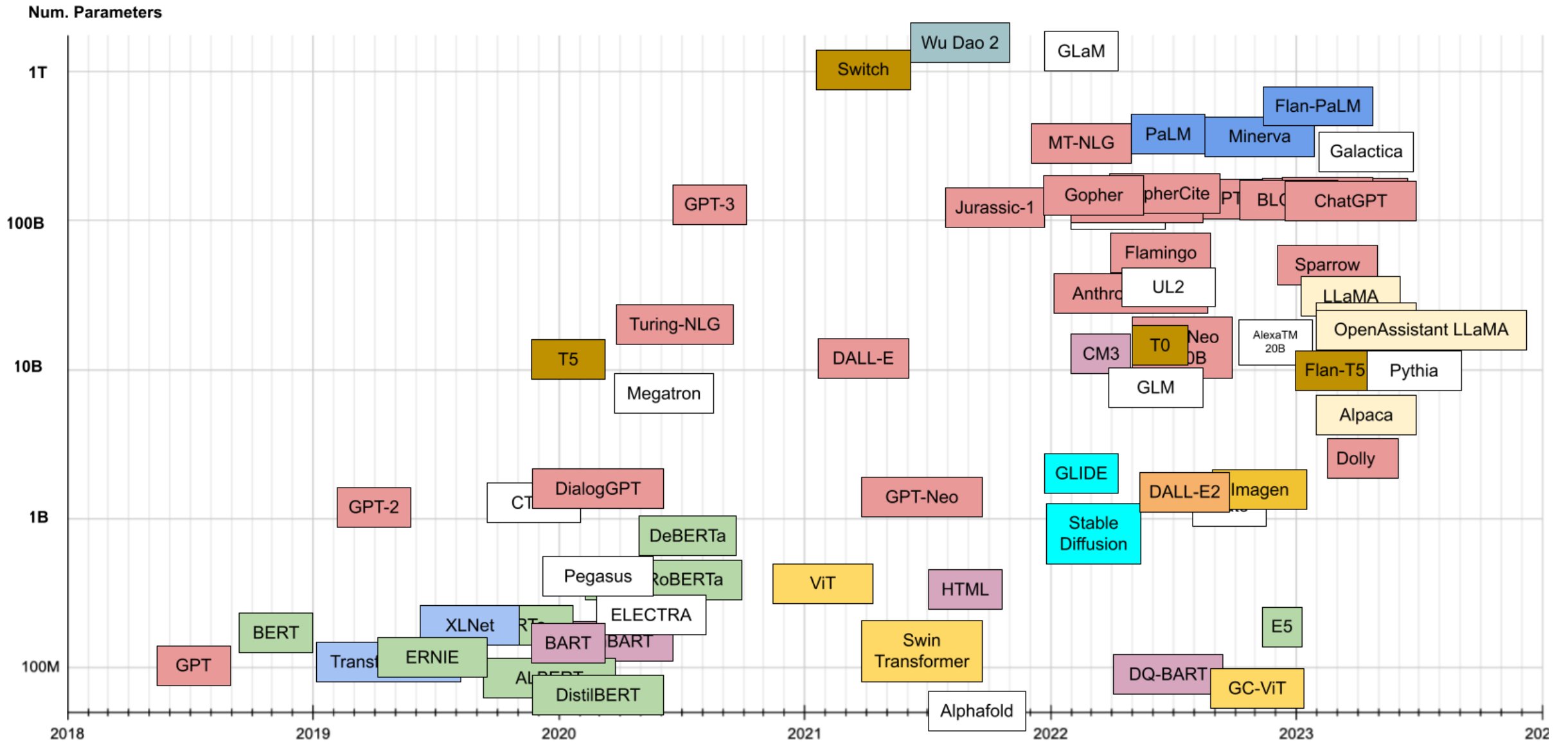
BERT Family of Models

- Encoder-only
 - Input: Corrupted version of text sequence
 - Goal: Produce an uncorrupted version of text sequence
- How to use:
 - Finetune for a classification task
 - Extract word/sentence embeddings

Some important BERT family members

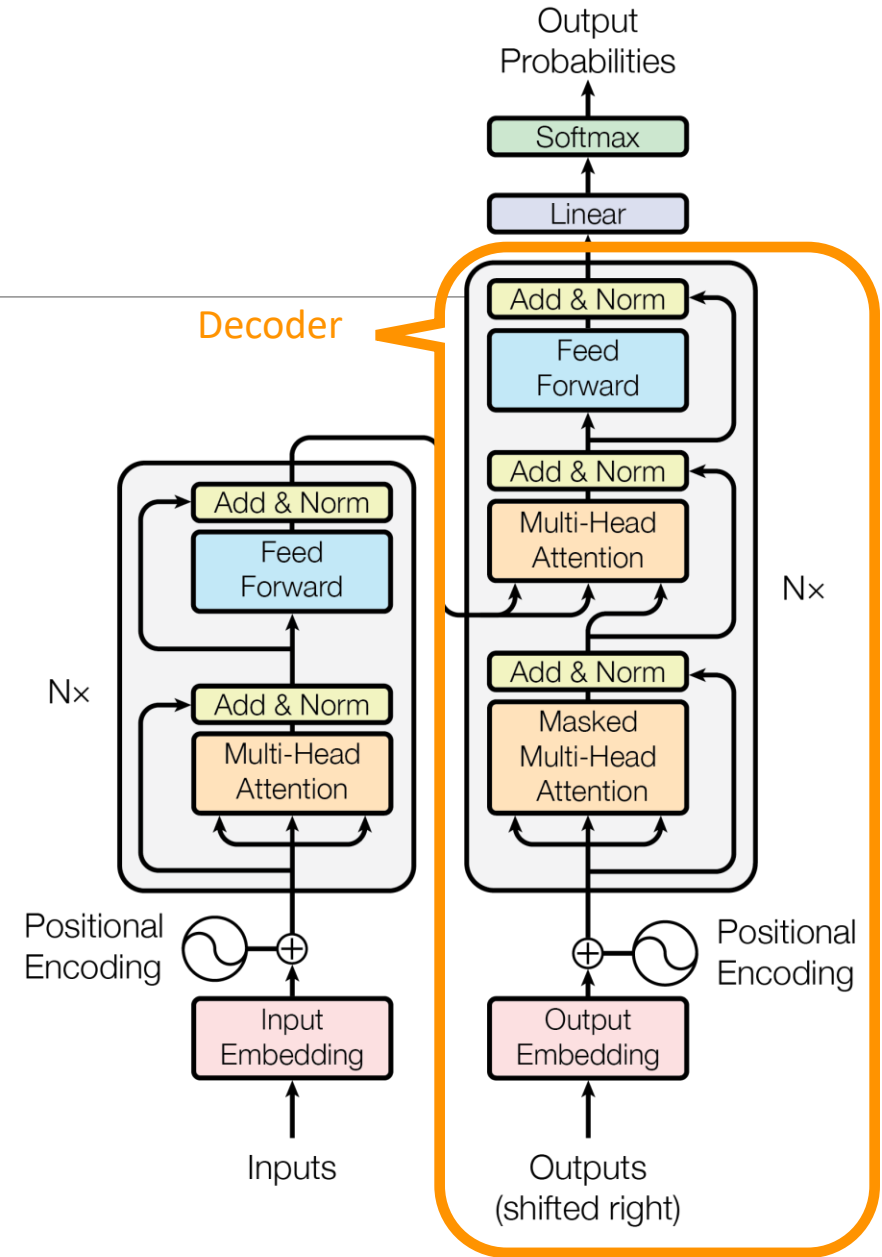
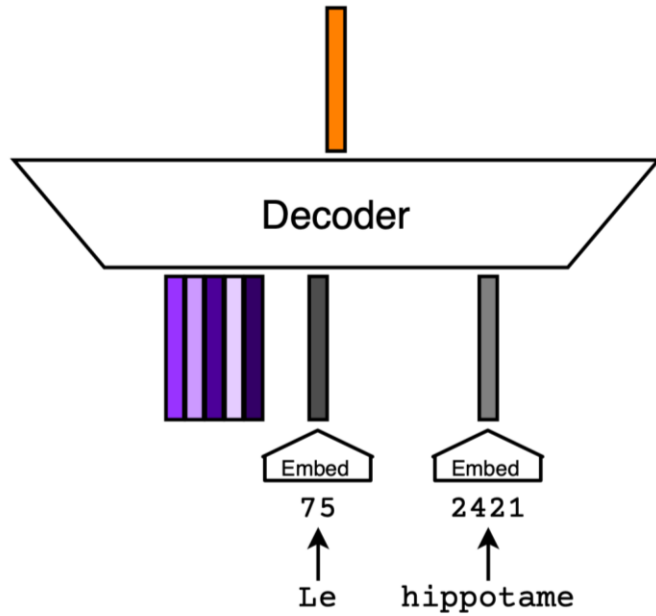
(in my opinion)

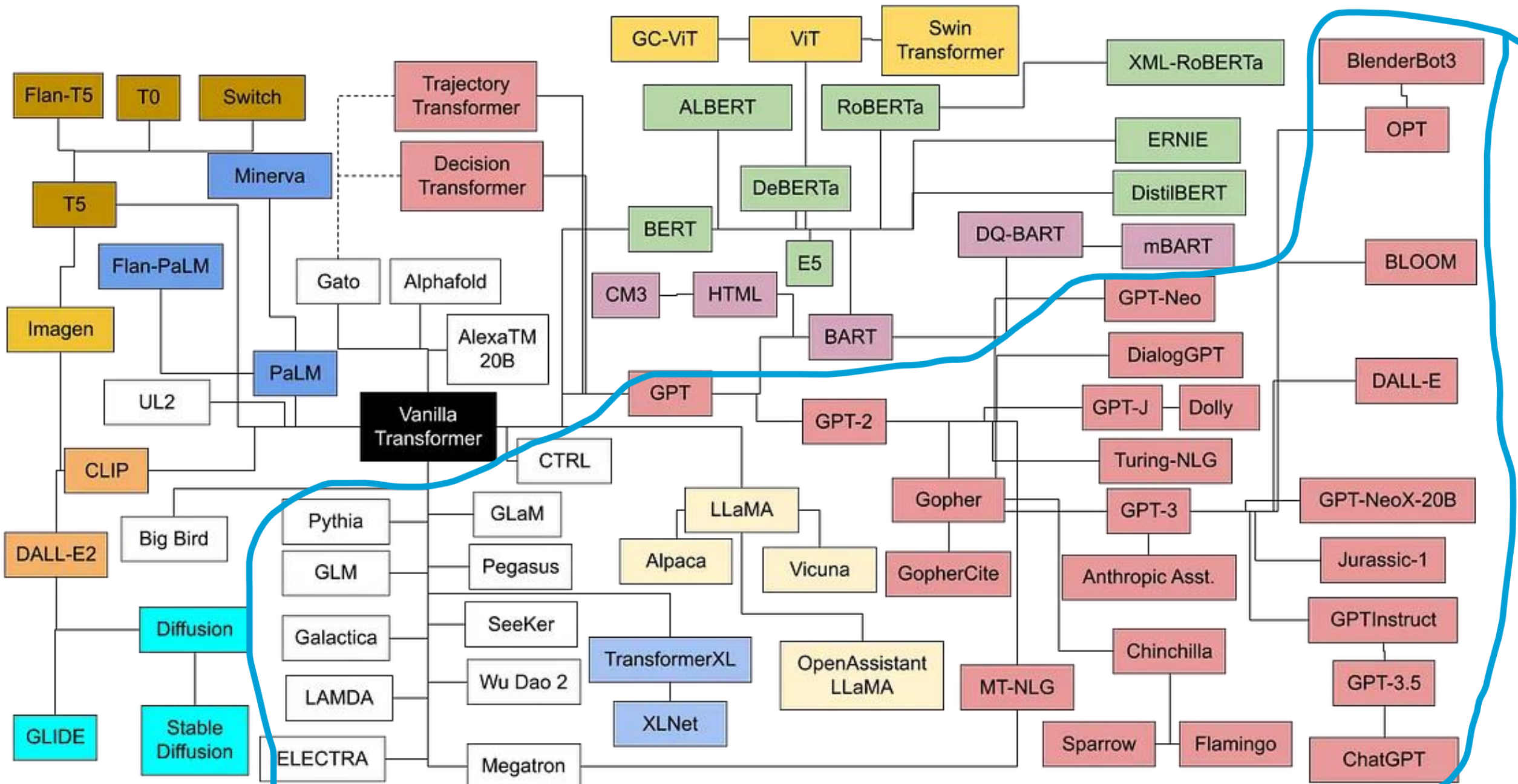
- RoBERTa (better version of the original BERT) – Liu et al. 2019 (Facebook)
- Sentence-BERT (BERT fine-tuned to give good sentence embeddings) – Reimers & Gurevych 2019 (Technische Universität Darmstadt)
- DistilBERT (lite BERT) – Sanh et al. 2019
- ALBERT (lite BERT) – Lan et al. 2020
- HuBERT (BERT for speech embeddings) – Hsu et al. 2021



<https://amatriain.net/blog/transformer-models-an-introduction-and-catalog-2d1e9039f376/>

Decoder-Only Models





<https://amatriain.net/blog/transformer-models-an-introduction-and-catalog-2d1e9039f376/>

GPT Family

- Decoder-only
 - Input: Text sequence
 - Goal: Predict the next word given the previous ones
- How to use:
 - Ask GPT* to continue from a prompt.
 - Finetune smaller GPTs for more customized generation tasks.
 - ChatGPT cannot be finetuned since it is already finetuned
 - Use OpenAI's API to get them to fine-tune GPT-3 for you.

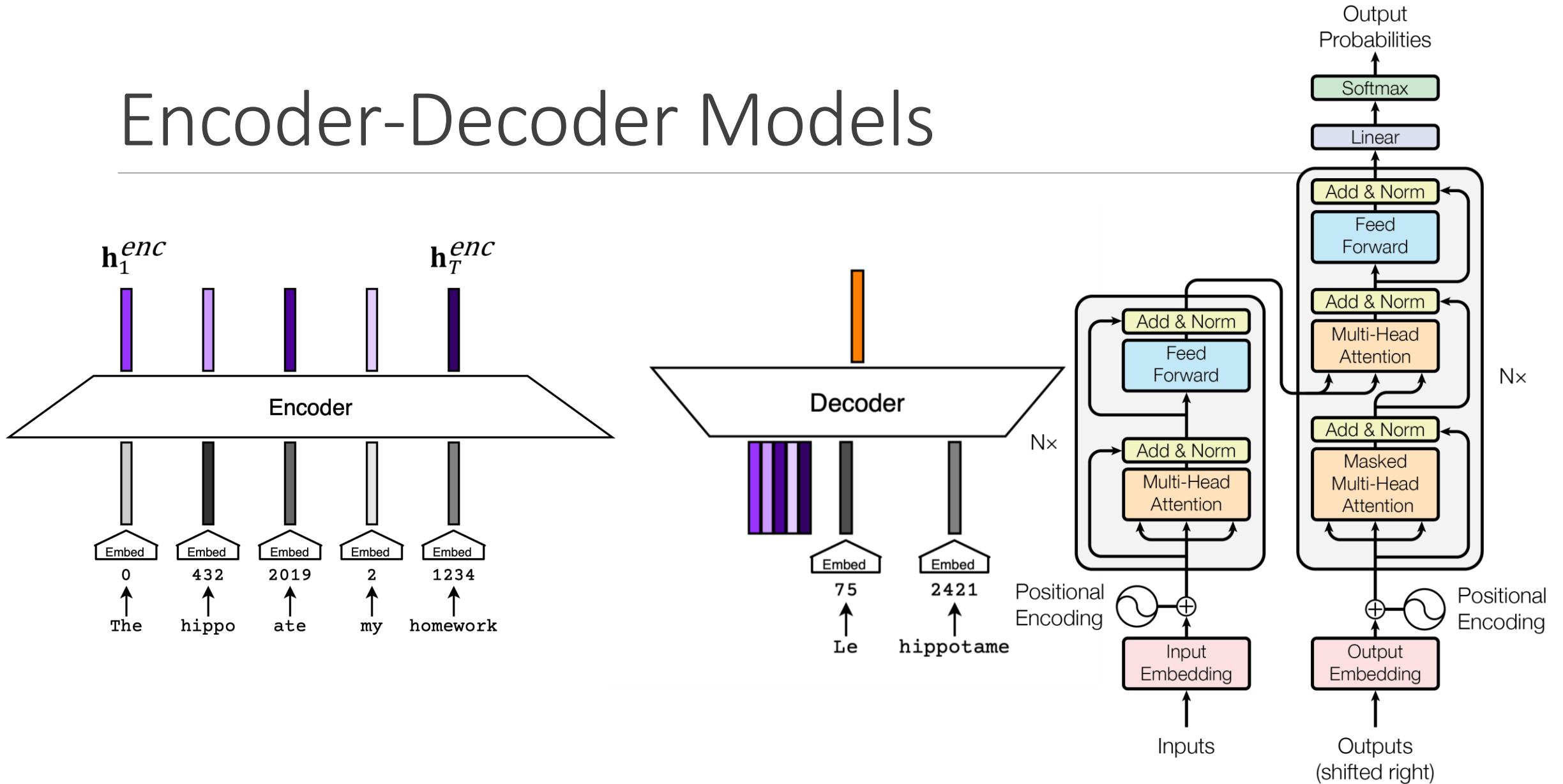
Some Decoder-Only Models

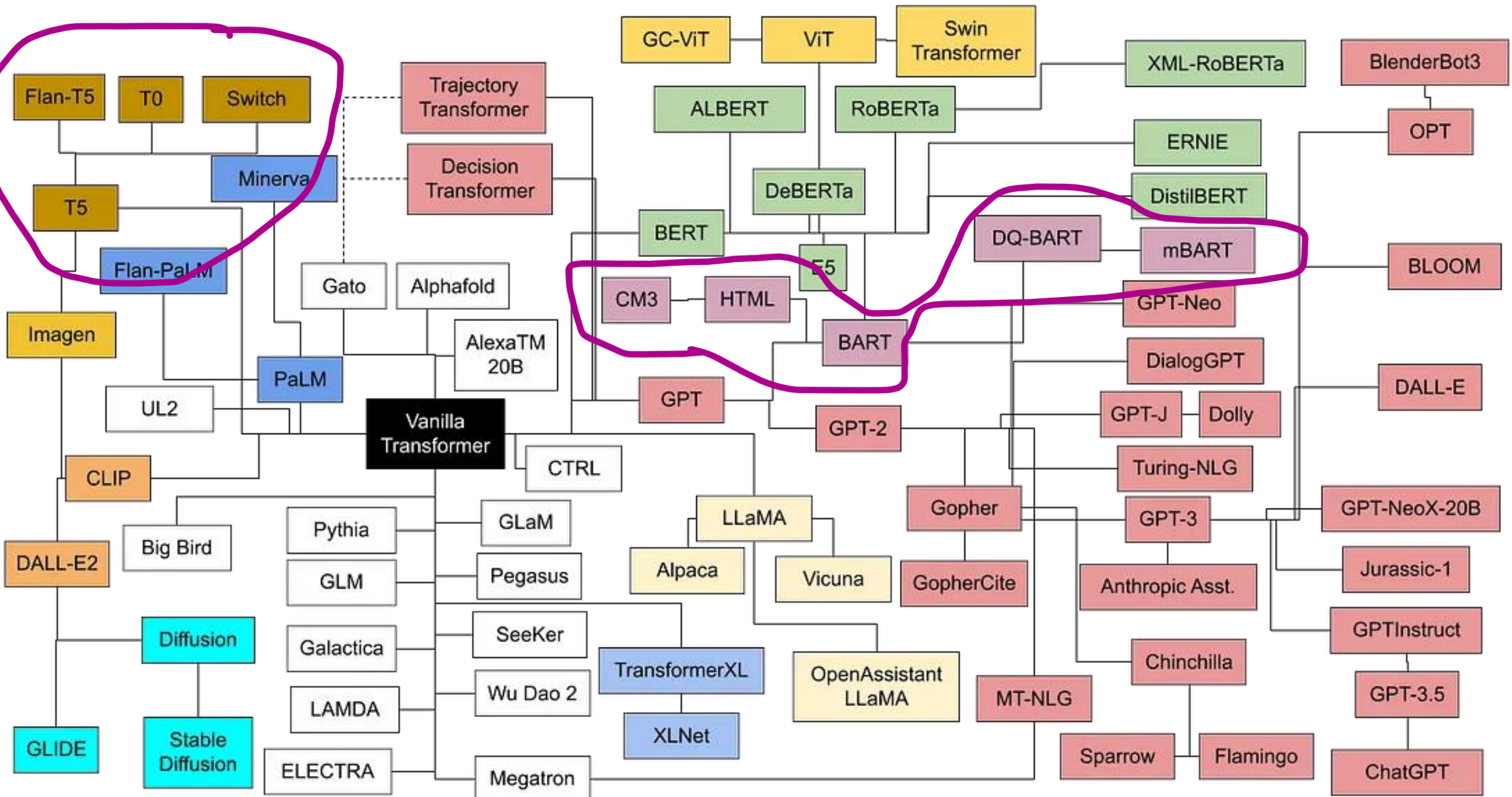
LLaMA (Meta)

GPT family (Open AI)

LAMDA (Google)

Encoder-Decoder Models





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Some important Enc-Dec family members

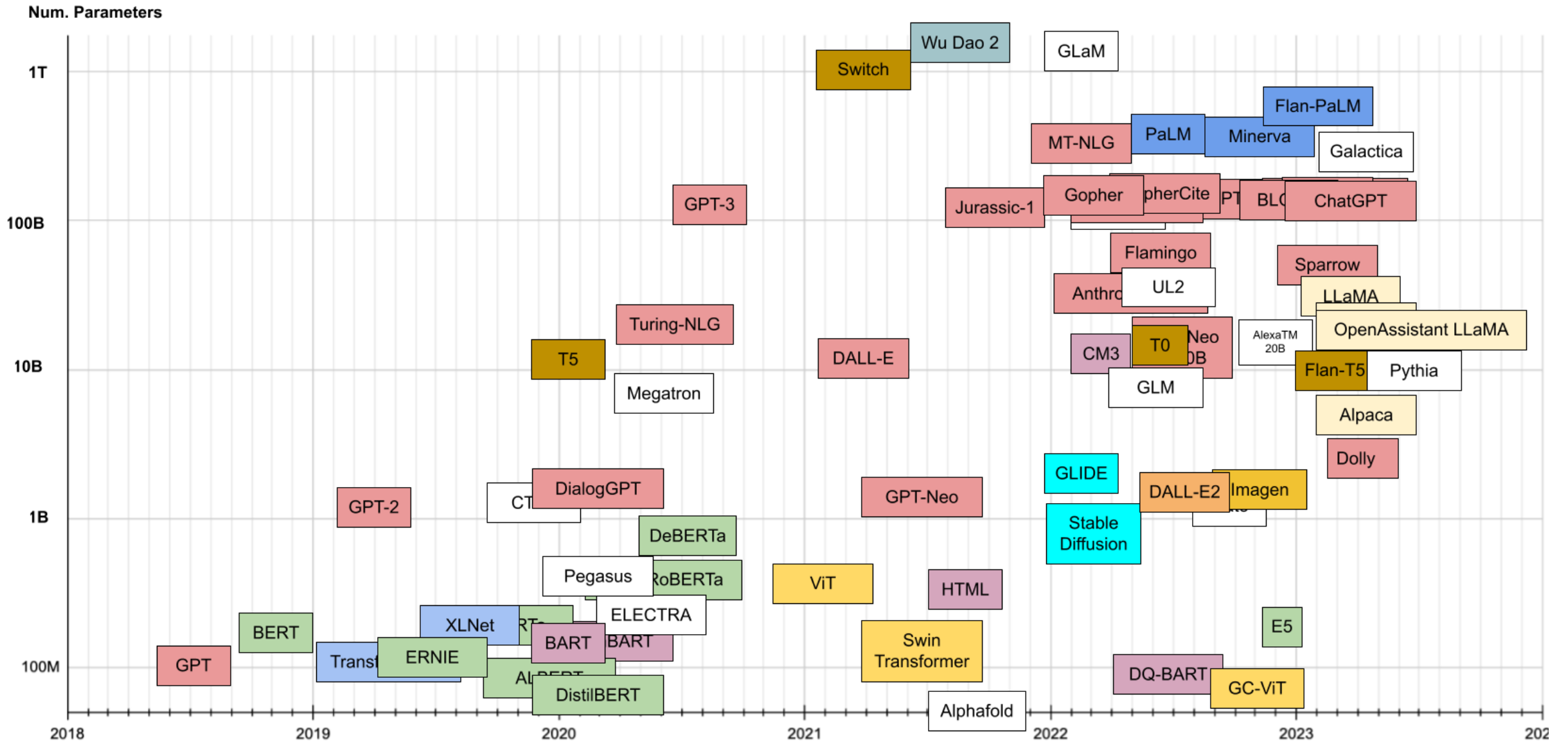
(in my opinion)

- T5 – Raffel et al. 2020 (Google)
- BART (combo of GPT and BERT) – (Facebook)

- DALL-E 2 (for caption prediction)

T5 Family of Models

- Encoder-decoder
 - Input: Text sequence with random word spans deleted
 - Goal: Generate the deleted word spans
- How to use:
 - Finetune smaller ones for either generation or classification tasks.
 - Prompt tuning (train a sequence of embedding which get prefixed to the input)



<https://amatriain.net/blog/transformer-models-an-introduction-and-catalog-2d1e9039f376/>